A methodology for eliciting, encoding and simulating human decision making behaviour

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Abstract

Agent-based models (ABM) are an increasingly important research tool for describing and predicting interactions among humans and their environment. A key challenge for such models is the ability to faithfully represent human decision making with respect to observed behaviour. This thesis aims to address this challenge by developing a methodology for empirical measurement and simulation of decision making in human-environment systems. The methodology employs the Beliefs-Desires-Intentions (BDI) model of human reasoning to directly translate empirically measured decision data into artificial agents, based on sound theoretical principles.

A common simulated decision environment is used for both eliciting human decision making behaviour, and validating artificial agents. Using this approach facilitates the collection of decision making narratives by way of participatory simulation, and promotes a fair comparison of real and modelled decision making. The methodology is applied in two case studies: One to carry out a trial involving human subjects solving an abstract land-use problem, and another to examine the feasibility of up-scaling the methodology to a real agricultural scenario—dairy farming.

Results from the experiments indicate that the BDI-based methodology achieved reasonably direct encoding of decision making behaviour from elicited human narratives. The main limitations found with the technique are: (1) the significant use of subjects’ time required to elicit their decision making behaviour; (2) the significant programming effort required; and (3) the challenge of aggregating behaviour from multiple subjects into a generalised decision making model. In spite of its limitations, BDI has shown its strengths as a tool for empirical analysis and simulation of decision making in research of human-environment systems.
Acknowledgements

I would like to express a great thanks to my supervisors Dr William Mackaness, Dr Femke Reitsma, Dr Michael Ravotsos and Dr Andy Dugmore for their constant support and mentoring throughout the project.

Femke Reitsma was a very motivating principal supervisor during the first half of the project and provided lots of useful advice. Her modelling experience proved to be of great value. She also provided me with many hours of demonstrating work to help me fulfill my teaching obligations. Finally, she always insisted on picking up the tab in our many meetings over lunch. A huge thanks Femke.

Thank you to Andy Dugmore, whose many creative ideas during our meetings in the early stages of the PhD provided a great source of inspiration in my search for a specific project.

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While William Mackaness has been a constant source of support during the project, he unexpectedly had to take on the duties of primary supervisor late in the project. During these final crucial months of write-up he has taken the time to arrange frequent meetings and to look over drafted thesis material. It has been a significant time commitment for an already busy lecturer and I’m very thankful for it. William was also instrumental securing the project initially, allowing me to present my ideas to the department and construct a PhD project around them. A huge thanks for this great opportunity.

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Thanks also to the students who kindly agreed to take part in the abstract land use experiments. Their narratives provided a good quality source of data for interpretation and eventually encoding into behavioural agents. Their enthusiastic participation made
the abstract land use experiments a success.

During development of the simulated dairy farm Desree Romer with her veterinary expertise provided a great wealth of knowledge on dairy farming to ensure the model was realistic. She took the time to show me around Crichton Royal Farm, and on several occasions helped with model testing, informing me of errors and suggesting improvements. Her help was very much appreciated.

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Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(Conrad Rider)
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Chapter 1

Introduction

With a growing number of agent-based models (ABMs) being used to study human-environment systems, there is greater need to formalise the process of ABM development. In particular, the technique used to simulate human decision making within these models needs better grounding in current psychology and artificial intelligence theory. Currently, many models adopt simplistic methods based on early theories of perfect rationality and utility maximisation (Monticino et al., 2007; Brown and Robinson, 2006; Barbier et al., 2005). It has been shown that such theories are a poor approximation of human behaviour (Ebenhoh, 2005; Stanovich and West, 2000), while several more in-depth theories have now surpassed them. Notably that of bounded rationality, and the beliefs-desires-intentions theory of human reasoning (Gigerenzer and Todd, 2000; Bratman, 1987). These theoretical developments have also been accompanied by developments in computer science, ranging from techniques such as heuristics, fuzzy reasoning and Markov decision processes, all the way to fully-fledged reasoning architectures based on the BDI and connectionist paradigms (Ingrand et al., 1992; Anderson et al., 2004).

Although they are known to provide better approximations of human decision making these more advanced techniques enjoy little use within agent-based models of human-environment systems. This is often because too much attention is paid to the empirical aspect of the research, without enough consideration of the alternative modelling techniques available and their different demands for empirical data. In essence, the model needs more influence on the type of empirical data gathered, rather than the empirical data constraining the type of model which can be used.
1.1 Project Aim

This project aims to address the disconnect between empirical data and simulated agent model by developing a methodology for empirical measurement and simulation of human decision making. The methodology will use a psychological model of human decision making, along with a rigorous process of behaviour elicitation and encoding to provide a direct as possible route from empirical data to programmed agent. The methodology will be designed specifically for use by researchers wishing to simulate the behaviour of human decision makers within a human-environment system.

1.2 Project Goals

In order to meet the aims of the project these four high-level project goals have been set out:

1. To find an appropriate theoretical model for the simulation of human decision making, sufficiently grounded in accepted decision making theory, and suitable for use within empirically based research.
2. To develop a methodology for elicitation of decision making behaviour in a form which is easily translated into the kind of data that the decision making platform uses.
3. To test the methodology with real human decision makers, and the use of appropriate validation procedures.
4. To test the feasibility of using the methodology within a complex human environment such as land use.

1.3 Structure Outline

The thesis is broadly arranged into four sections:

1. Introduction to the background with a review of current literature.
2. Presentation of the core methodology being tested.
3. Description of the case study experiments done to test the methodology.
4. Discussion of the results and their implications for the wider research field. These sections are discussed in more detail below.

1.3.1 Background and Reviews of Literature

This interdisciplinary project brings together two distinct research areas. (1) The field of artificial intelligence and psychology, which investigates how humans make decisions and the theory underlying the decision-making process. (2) Research of land use change using agent-based simulations of the decision makers who influence the changes. These sections introduce the key concepts and areas of research in both fields, citing and analysing the recent literature.

1.3.2 Elaboration of the Core Methodology

This section details the core methodology applied in the project: Construction of artificial human-like BDI agents using decision narratives from real decision makers. It introduces previous work which inspired the methodology, describes exactly how it works, and critically analyses the strengths and weaknesses of the system with respect to alternative methods used.

1.3.3 Case Studies

Two case studies are presented in the thesis. The principal study was aimed at developing and testing the designed methodology. It involved an abstract land use simulation and the use of university students to capture decision making behaviour. Their behaviour was then analysed and encoded into artificial BDI agents designed to mimic their behaviour. The second case study aimed to show the feasibility of up-scaling these experiments to an applied domain as complex as dairy farming. It involved the construction of a full and realistic dairy farm simulator which could be used in experiments to analyse and simulate the decision making behaviour of dairy farmers. During the study, participatory simulation experiments with dairy farmers were carried out. Narrative data from the experiments were analysed to create agent schemas describ-
ing the participants’ behaviour. Unfortunately, due to resource constraints it was not possible to implement these behaviours as executable agent programs.

1.3.4 Discussion and Conclusions

These final two sections analyse the results gained from experiments in more detail to provide a measure of how well the methodology performed. The suitability of the method to particular domains is discussed, and its shortcomings and merits are compared to those of alternative techniques.
Chapter 2

Review of Decision Modelling in Applied Agent-Based Models

2.1 Introduction

Agent-based models (ABM) have become an increasingly important tool in research on coupled human-environment systems. They are particularly suited to the task because they specifically represent the decision making of individuals, as well as their interactions with others and the environment. This allows them to simulate the complex emergent behaviour of human societies; its effect on their surrounds; and the continuous feed-backs which occur between human activity and the changing environment (Matthews et al., 2007; Clifford, 2008; Evans and Manson, 2007).

Within the ABMs themselves there are a great many techniques which can be used to simulate individual agent behaviour (or decision making). They range from simple, reactive rule-based systems; to utility-based decision theoretic models; intentional, models with goal-directed reasoning; or even cognitive models designed to emulate brain function. Each technique has its own merits and downfalls, and will be better suited to certain applications, while not well suited to others. Choosing the appropriate decision modelling technique is important because it can have a significant impact on the effectiveness of the model (Dent et al., 1995).

This chapter will briefly review some agent-based models designed to simulate a human-
environment system, analysing the way in which decision making is represented. It will broadly categorise the methods used, providing a critique of their application.

### 2.2 Applications of Human-Environment ABMs

A popular use for applied ABMs is in land use modelling—both urban and rural (Riveira and Maseda, 2006; Parker et al., 2003; Verburg et al., 2004; Briassoulis, 2008; Matthews et al., 2007). Its wide adoption in land use research is due to land use being a social, human driven phenomenon, with the land environment both responding to and affecting decision making. ABM is well suited to representing the complex social and economic interactions of land use decision makers and the feedbacks between land use decision making and its environmental effects.

Outside of the land use field, ABMs of human-environment interactions are used to study settlement, innovation diffusion, social networks, and war/combat scenarios (Deffuant et al., 2005; Alam et al., 2009; Cil and Mala, 2010). Although the technique has proved to be useful in these areas, there appears to be markedly fewer publications of ABMs outside of land use research. This may in part be related to the scale of land use research and not just the suitability ABM to the domain.

### 2.3 Models From the Literature

Ten applied ABMs of human-environment systems were carefully selected from the literature for review. Tables 2.1 and 2.2 summarise the reviewed models with respect to eight characteristics.

1. **Purpose**: The general purpose of the model. What research question it answers.
2. **Explanatory/Descriptive**: Related to purpose, this says whether the model is designed to re-create reality with some degree of accuracy (descriptive), or whether it explores a particular theoretical phenomenon in isolation to measure its characteristics (explanatory).
3. **Environment**: Describes the surroundings in which the agent makes their decisions.
4. **Decision Algorithm**: This key field describes the technique used to enable the agent to generate decisions and ultimately actions, allowing it to act autonomously within its environment.

5. **Cognitive Faculties**: These are features within the agent’s decision algorithm which mimic known human cognitive abilities. Examples include memory, learning, reasoning and planning.

6. **Heterogeneity**: Describes whether the model represents variation among the agents, or whether they all make decisions in the same way. Heterogeneity can be categorical or individual.

7. **Environment Interactions**: The interactions the agent makes with its environment.

8. **Agent-agent Interactions**: Any interactions the agent makes with other agents. In its looser form, agents sense changes in the environment which came about from actions made by another agent. In its strongest form agents communicate and negotiate directly with each other.

### 2.3.1 Model Selection Criteria

The basic criteria used to select appropriate models from the literature were that they: (1) are agent-based, with the agents representing humans; (2) were applied to the study of a coupled human-environment system. ‘Environment’ here need not be the natural environment, but any environment in which humans are situated. For example, the built environment, a combat situation, a business or economic environment, or even a political one.

Aside from these specific requirements, a greater priority was placed on ‘descriptive’ models. The reason they are more useful in this review is that they generally strive to create a realistic representation of human decision making. The way in which models achieve this is the key subject under review. Although exploratory models may sometimes use theories of human decision making to inform their design, the ability to reproduce realistic decision making behaviour is not always a requirement.

Table 2.1 lists the models reviewed and their basic properties and Table 2.2 shows

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1. Description here means the model attempts to re-create the system realistically enough that it has some degree of predictive power.
details of the decision algorithm and its properties.
Table 2.1: Agent-Based Models – Basic Properties

<table>
<thead>
<tr>
<th>Model – Paper(s)</th>
<th>Purpose</th>
<th>Explanatory or Descriptive</th>
<th>Environment</th>
<th>Environment Interactions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bithell and Brasington (2009)</td>
<td>Understanding the effect of human society on a forested ecosystem with a focus on hydrology.</td>
<td>Model is said to be closer to explanatory rather than descriptive.</td>
<td>Mountainous rural landscape individual-based forest model driven by a cellular hydrological sub-model.</td>
<td>Settlement (stochastic), felling trees for firewood (stochastic movement) and clearing for land, land use selection (maize or rice).</td>
</tr>
<tr>
<td>Barnaud et al. (2008)</td>
<td>Aiding decision making of local farming community members to help protect their environment.</td>
<td>Not specifically stated, but descriptive given the goals of the model.</td>
<td>Spatial grid of cells, each representing farming fields. Randomly fluctuating rainfall and market conditions, and labour market.</td>
<td>Hunting for a credit source from banks or usurers, allocation of fields to land use, allocation of labour to farming activities (on an annual basis).</td>
</tr>
<tr>
<td>LUDAS (Le et al., 2008)</td>
<td>To provide decision support for land managers’ plans. Examining the outcomes of policy.</td>
<td>Not specifically stated but given the purpose, model probably designed to be descriptive.</td>
<td>Spatial raster grid with layers corresponding to modelled economic and environmental conditions. Land cover on each cell develops autonomously according to a cellular automaton model.</td>
<td>Collecting forest products, making land use selections, allocation of labour.</td>
</tr>
<tr>
<td>CybErosion (Wainwright, 2008)</td>
<td>Explaining the effects of anthropic pressure on landscape evolution. Focused representing interactions between land, vegetation, animals and people.</td>
<td>Explanatory. Does not aim to reproduce the land-form evolution exactly, only demonstrate effects of human and animal interactions with the landscape.</td>
<td>Cellular model based on a DEM (digital elevation model). Each cell describes soil properties and vegetation type/properties. Landscape also contains agent-based modelling of farmed and wild animals.</td>
<td>Movement through landscape, hunting animals, clearing vegetation/cultivation.</td>
</tr>
<tr>
<td>MABEL (Alexandridis and Pijanowski, 2007; Lei et al., 2005)</td>
<td>To describe parcel-based land use evolution.</td>
<td>Descriptive (with respect to land parcel partitioning/evolution).</td>
<td>Vector-based land parcels with associated geographic and biophysical properties.</td>
<td>Partitioning and combining land parcels, management of owned land parcels.</td>
</tr>
<tr>
<td>IMSHED (An et al., 2005)</td>
<td>Impact assessment of growing rural population on forests and the panda habitat.</td>
<td>Descriptive: given the use of validation with empirical data, model is designed to be predictive.</td>
<td>Raster-based grid of cells, with each cell/pixel representing elevation, slope, land cover and tree density. Tree density driven by forest growth sub-model.</td>
<td>Collection of firewood from the environment, switching to electrical power supply.</td>
</tr>
<tr>
<td>Model</td>
<td>Authors</td>
<td>Description</td>
<td>Environment Details</td>
<td>Agent Actions</td>
</tr>
<tr>
<td>-------------</td>
<td>-----------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------</td>
<td>---------------</td>
</tr>
<tr>
<td>SYPRIA</td>
<td>Manson (2005)</td>
<td>Evaluating the use of genetic programming to model decision making in coupled human-environment systems.</td>
<td>A 2D grid of cells maintaining the state of land-use, coupled with a cellular automata model, simulating the effects of soil fertility, crop and vegetation growth.</td>
<td>Selection of land use and implementation of land management. Agents assess the suitability of land for particular uses by sensing various environmental factors such as soil fertility, land elevation, slope aspect, land cover and cell distance.</td>
</tr>
<tr>
<td>FEARLUS</td>
<td>Polhill et al. (2010)</td>
<td>Generate possible scenarios of future land use in the Grampian region.</td>
<td>Environment consists of a spatial grid of cells, with each cell characterising a range of biophysical properties and configurable with a range of possible land uses. Also consists of climate and ecology drivers which vary temporally.</td>
<td>Selection among possible land uses for each cell. Agents sense yield and economic return value from each cell.</td>
</tr>
<tr>
<td>Norling</td>
<td>(2004)</td>
<td>Extending the BDI framework to include effects of learning from past experience.</td>
<td>Simulated 3D combat environment, composed of rooms, hallways and platforms. Useful items can be collected from various positions within the environment.</td>
<td>Movement through space restricted by objects and boundaries, collection of items, loss of health within hazardous areas.</td>
</tr>
</tbody>
</table>
### Table 2.2: Agent-Based Models - Decision Making Properties

<table>
<thead>
<tr>
<th>Model - Paper(s)</th>
<th>Decision Algorithm</th>
<th>Cognitive Faculties</th>
<th>Heterogenity</th>
<th>Agent-agent Interactions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bithell and Brasington (2009)</td>
<td>Rule based, using a stochastic navigation algorithm.</td>
<td>Purely reactive.</td>
<td>All agents initialised, and process identically. Only heterogeneity is that imposed by surroundings/environment.</td>
<td>No direct communication. Indirect interaction through resource competition.</td>
</tr>
<tr>
<td>Barnaud et al. (2008)</td>
<td>Rule-based, using static threshold rules for credit.</td>
<td>Purely reactive.</td>
<td>Heterogeneity, based on categories of agents (farmers, type A, B and C) initialised with different amounts of land and capital resources. Each farmer type uses same decision making process, with only state (socioeconomic conditions) affecting outcome. Decision making is purely driven by available finances and labour.</td>
<td>Agents use ‘acquaintances’ (other agents) as another source of financial credit.</td>
</tr>
<tr>
<td>LUDAS (Le et al., 2008)</td>
<td>On a household level. Hybrid (rule-based, built on top of utility maximisation implemented with multi-nominal logistic functions). Uses stochastic selection amongst probabilistically weighted alternatives to make final choice.</td>
<td>Purely reactive.</td>
<td>Category-based, initialised with varying state variables. Agents change category during simulation.</td>
<td>Interactions based on reading status of other agents (i.e. land ownership). No actual communication.</td>
</tr>
<tr>
<td>CybErosion (Wainwright, 2008)</td>
<td>Operates under a simple set of rules.</td>
<td>Purely reactive.</td>
<td>No heterogeneity apart from male/female.</td>
<td>No human-human interactions are simulated, but human-animal interactions are. Highlights a general criticism of agent-based models in that they often omit the all-important human-human interactions which characterise their complex behaviour (see p671).</td>
</tr>
<tr>
<td>MABEL (Alexandridis and Pijanowski, 2007; Lei et al., 2005)</td>
<td>Besian belief network, utility maximisation, BDI (implementation details not given).</td>
<td>Memory (belief base), Goal directed reasoning.</td>
<td>Categorised into base (farmers, urban residents, foresters etc) and non-base agents (policy makers, planners) Each base agent also takes on characteristics depending on the land parcels it owns.</td>
<td>Negotiation between buyer and seller agents for buying and selling of land parcels.</td>
</tr>
<tr>
<td>Model</td>
<td>Author(s)</td>
<td>Decision Making Approach</td>
<td>Heterogeneity</td>
<td>Interactions</td>
</tr>
<tr>
<td>-------</td>
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<td>---------------</td>
<td>-------------</td>
</tr>
<tr>
<td>IMSHED (An et al., 2005)</td>
<td>Rule-based decision making, with use of a discrete choice logit-model to calculate probability of switch to electricity. At household level.</td>
<td>Purely reactive.</td>
<td>No process based or categorical heterogeneity, only state-based heterogeneity.</td>
<td>Agent-agent interactions not modelled.</td>
</tr>
<tr>
<td>SYPRIA (Manson, 2005)</td>
<td>Multi-criteria evaluation of a set of factors and constraints. Weights are applied to each factor to determine suitability of a land cell to each of the possible land uses. Weight values are evolved individually for each agent over time using natural selection.</td>
<td>Evolutionary adaptation in successive generations simulates inter-generational learning.</td>
<td>State-based heterogeneity. Weights applied to each factor determining suitability are unique to each agent.</td>
<td>No direct agent-agent interactions, however ‘actors’ are influenced by decisions of rule-based ‘institution’ agents.</td>
</tr>
<tr>
<td>FEARLUS (Polhill et al., 2010)</td>
<td>Two categories of agents. One category has agents which use a heuristic or ‘rule-based’ decision making. The other category of agents uses a CBR (Case-Based-Reasoning) algorithm.</td>
<td>First category are reactive. Second category maintain episodic memory of past decisions, and use utility-based reasoning to select appropriate actions.</td>
<td>Algorithmic heterogeneity between the two categories. State-based heterogeneity among individuals in each category.</td>
<td>Trading of land parcels among agents. Receipt of reward for low pollution from a ‘government’ agent.</td>
</tr>
</tbody>
</table>
2.4 Explanatory vs Descriptive Models

For many models one of the ultimate goals is predictive power. If a model is capable of being initialised with empirical data, and able to predict the future scenarios resulting from it, then it is often considered a success. However, predictive power alone may not be enough to explain why the outcomes are as they are. In order to implement actions or policies to have any kind of effect on the system in question, it is often necessary to understand how it behaves in the way it does. This can only be achieved if the model has some level of explanatory depth (Beven, 2001).

Models with explanatory depth are usually based upon a theory used to explain how the component processes interact to generate an outcome. Often these theoretical models are equation-based with various parameters representing empirically measurable values. Although equation-based approaches work for a vast range of systems, they may not be as well suited to modelling complex systems. These are systems which exhibit patterns of chaos and self-organisation, and are characterised by processes which feed back on each other. With its vast number of interconnected neurons, the human brain is also a complex system. The consequence of this is that a solely equation-based approach may not be adequate for describing human decision making if an explanatory model is sought.

More often than not, explanatory models tend to simplify by reducing the number of components considered or narrowing scope. Usually this is at the expense of predictive power. Many decision models in the agent-based modelling literature use simple reflex/rule based algorithms as a way to improve their explanatory ability (Bithell and Brasington, 2009; Wainwright, 2008). In these cases, the models aim to be explanatory in terms of agent-environment interactions rather than in terms of internal agent decision making. A reflex-based agent is generally considered a poor approximation of human decision making. Apart from the model by Norling (2004), none of the reviewed models attempted to use an explanatory model of human decision making.

Looking at the purpose of many of the reviewed ABMs, it is clear that the majority aim to either test the effect of policy on the state of the modelled system, or describe possible future scenarios resulting from the effects of various anthropogenic pressures. Their research goals mean they tend to be more descriptive than explanatory. Because these goals require a model which is predictive to some degree, it is necessary for their outputs to be believable and translate to the real world system. In such cases, the decision models do not necessarily need to be explanatory, but they do need a model which will behave in a human-like manner. Even in these ‘descriptive’ studies, an explanatory decision making model can be useful, particularly where the study of
policy effects is concerned.

2.5 Environments and Environmental Interactions

The environments used in agent-based models are important from a decision modelling perspective. A decision model must make sense of various properties in the environment, and then must generate actions which have an effect on that environment. The former often requires an ability to consolidate the detail within the environment to generate abstract and meaningful concepts. The latter requires an understanding by the agent model on how actions will affect the environment to help further its goals. The more complex the environment, the more difficult it is to construct an agent with these abilities (also known as grounding).

From the models reviewed, the majority of spatial environments discretise space into a grid of cells, with each cell maintaining environmental properties for the area concerned. Some of these properties are constant; others may be dynamic but driven by predetermined data or rules; while in a more complex simulation cellular properties may be dynamic—driven by an environmental sub-model. In a smaller number of spatial ABMs the environment is represented as vector-based parcels. This gives way to more complicated topological rules and can complicate sub-models, so is only usually adopted if significant realism is lost by using a cellular representation. A classic example is the land ownership partitioning used by the MABEL model (Alexandridis and Pijanowski, 2007). Where spatially localised properties are modelled they may sometimes depend on properties of neighbouring areas. In such cases the model can be classified as a cellular automaton. These are important because the spatial feed-backs occurring can create non-linear behaviour with patterns of chaos or self-organisation.

2.6 Decision Modelling Approaches

Within the reviewed models, the following techniques were used to model the decisions (ordered by frequency):

- Rule-based (heuristics, decision trees, finite state machines, fuzzy logic)
• Utility functions (multi-attribute, linear programming)
• Beliefs-Desires-Intentions reasoning
• Reinforcement learning
• Genetic algorithms

Five out of ten of the models use rule-based decision-making at the top level. Of those five, two (LADUS and IMSHED) use mathematical optimisation techniques to facilitate rule resolution. Two models use optimisation methods at the top level of decision making (Evoland and SYPRIA). Use of sequential optimisation with Evoland results in a utility maximising agent model (or perfect rationality). The genetic algorithm used in the SYPRIA model causes the decision making algorithm to tend towards the optimal solution over time. However, it does not guarantee that optimality will be attained within finite time. In essence, it provides a form of bounded rationality (the bound being the level of optimality achievable within the time-frame of the simulation run). It also reproduces to some degree, a property of human society which allows learned knowledge to accumulate by being passed to successive generations. Recent research with the FEARLUS model also uses agents with a learning capability. It is implemented using a CBR algorithm which makes use of knowledge of previous decision cases to inform the current decision - a form of inductive reasoning. The final two models – MABEL and the model by Norling (2004) – use the BDI framework to implement agents with goal-directed reasoning. The former also implements a Bayesian belief network to allow representation of probabilistic beliefs. The latter extends BDI to allow adaptation of the context-based filtering mechanism (used during goal selection). It uses the Q-learning technique to provide the agents with a reinforcement learning capability.

What these techniques involve and how they are implemented is described in more detail in Chapter 3.

2.7 Rationality, Irrationality and Bounded Rationality

Agent decision models using utility maximisation functions, such as linear programming and other optimisation techniques are making two controversial assumptions: (1) that humans make perfectly rational decisions and (2) humans may apply unlimited re-
sources and advanced analytical techniques to their decision making (Gigerenzer and Selten, 2001; Colman, 2003).

Some studies propose that instead of perfect rationality, humans actually make irrational decisions (Monticino et al., 2007). From a practical perspective this assumption can be problematic for model validation, since any behaviour which is not rational may be deemed as valid. A decision which is irrational is not entirely based on sound logical reasoning. Such reasoning can produce any outcome, depending on the specific logical error causing irrationality. The most basic agent program which simply makes randomly chosen decisions (analogous to tossing a coin) would produce output which cannot be proved valid or invalid. When seemingly irrational decisions are caused by partial or incorrect knowledge, rather than a fundamental fault at the reasoning level, this is bounded rationality. The capacity to make the correct decision is bounded by limited knowledge available.

Unlike irrationality, bounded rationality dictates that agents are rational, but only to the point that is feasible with knowledge and resources available (Herbert, 1982). This may indeed result in ‘random’ decisions, for example where a snap decision needs to be made on the spot, without any time or information to make an informed one. Not many, but some human decisions are like this. For example, the selection among seemingly equal length queues at the supermarket. However, they are not random because the decision maker is behaving irrationally. Rather, a lack of knowledge or time do not allow for any meaningful deliberation. If a decision must be made one way or the other (without any reference to external stimulus or internal state/knowledge), then it is quite possible for repeated measurements of that decision to exhibit no measurable pattern.

The concept of ‘boundedly rational’ agents appears quite often in the literature. A problem is that it is sometimes used to account for limitations in the model, rather than real limitations observed in human decision making. For example, a land use model exploring rural/urban fringes by Parker and Meretsky (2004) uses a utility maximisation approach, based on perfect visibility of neighbouring agents’ land use decision making behaviour. However, the paper later states that the agents are boundedly rational because they cannot predict future land use choices of neighbours. There is no explanation as to why this limitation was imposed. It appears to be a choice based on a technical limitation in the model, rather than a scientifically understood phenomenon.
2.8 Cognitive Faculties

It is known that humans make use of various cognitive abilities during decision making; including memory, reasoning and learning (Koechlin and Hyafil, 2007). The performance of each of these faculties within our brains has a direct effect on our ability to make good decisions. As a result, it is likely that the degree to which each of these are simulated within an artificial agent will have an impact on the level of realism, and ultimately the predictive power of the model.

On examining the models reviewed, the majority do not appear to represent the aforementioned cognitive faculties. Seven out of ten models used optimisation, rule-based approaches, or a combination of the two. These models belong to a broader class of ‘reactive’ models. In such models memory is represented, but only in its shortest-term form. Memory is used to maintain state during rule resolution or utility calculations, but is not persistent between successive decision making iterations. In such reactive systems all data driving each iteration of decision making comes from the current state of the environment, rather than any previous internal state.

According to Kirwan (1995), reasoning is defined as: “the cognitive process of looking for reasons, beliefs, conclusions, actions or feelings.” Because all decision making agents (at a minimum) must process the perceived state of the environment to arrive at decisions and ultimately actions, they are all capable of ‘reasoning’ to some degree. Humans are capable of deductive, inductive, abductive and analogical reasoning. In order to simulate these types of reasoning behaviour, it is necessary for agents to posses an internal representation of knowledge. A reasoning engine may then apply logical inference or quantitative analysis to the knowledge to derive new knowledge, create decisions or take action (Russell and Norvig, 2003). Within the reactive models, no knowledge beyond quantitative perceptions of the current state of the environment is represented. The BDI-based models maintain a belief base and are able to carry out deductive reasoning by manipulation of these beliefs. It allows the agent to update the state of its beliefs, and select appropriate goals or select plans of action. This higher level of reasoning is a step closer to the complex sorts of reasoning thought to be used in human cognition. While BDI agents posses a more realistic form of decision reasoning, there is no agent learning capability included in the framework. As demonstrated in the model by Norling (2004), learning can certainly be ‘bolted on’
to a BDI agent. However, it should be noted that the BDI theory itself provides no explicit learning mechanism.

Learning is explicitly represented within CBR-based agents in the FEARLUS model. The agents build up an episodic memory of past decisions, the state leading to them and the resulting outcome. This is then used to reason about future decisions. It mimics our natural ability to learn from past experiences, providing reinforcement of good decisions and repulsion of bad ones. Over time, the CBR agents accumulate enough past experience to make well-informed decisions, tuned to their current environment.

2.9 Agent Heterogeneity

Heterogeneity among agents may on the surface appear fairly clear cut. Either agents in the simulation behave the same (are homogeneous), or they behave differently (are heterogeneous). The problem is that differences in behaviour can be exhibited by agents running exactly the same algorithm. This is because algorithms also have context (or state). Behaviour is not only determined by the algorithm, but also by the state in which the algorithm is executing. State here refers to the values of variables read by the algorithm.

From an ABM perspective, differences in state might be things such as how much money, land, or labour an agent has. Differences between algorithms might be whether an agent uses utility maximisation, heuristics or fuzzy logic. Because differences in state give way to different behaviour, it may be considered that agents in a different state is all that is necessary to represent inter-agent heterogeneity. Consider an example where an agent has a simple bit, if set to 0, it behaves as prey, if set to 1 it behaves as a predator and consumes prey agents. A rule is then applied in the decision algorithm which causes an agent on an even square to become prey and on an odd square it becomes a predator. Is this agent heterogeneity? At any one time the agents will indeed exhibit behavioural heterogeneity. However, each agent will have exactly the same behaviour under the same conditions.

Truly heterogeneous agents may still execute the same algorithm, but must have differences in state which is immutable after agent initialisation. In other words, state variables affecting agent behaviour have different values assigned to different agents.
on initialisation and remain constant during execution. Citing the previous example, suppose half of the agents are *initialised* as prey and the other half are predators. If the pred-prey state bit is unchangeable during the simulation run, then the model’s ability to represent behavioural heterogeneity is assured.

In the models by Deadman et al. (2004) and Bithell and Brasington (2009), the agents are described as heterogeneous. However, the heterogeneity is brought about by differences in state which do not remain constant during the simulation run. Although these models create differences in behaviour, they are not persistently heterogeneous. It is possible for all agents within the model to exhibit exactly the same behaviour. It is analogous to two dogs which are exact clones of each other exhibiting different behaviour dependent on mood. Although differences in behaviour may be observed at any chosen instant, their behaviour will be exactly the same under identical conditions.

Where models do capture heterogeneity among agents, it can be broken down into two general types:

1. **Categorical**: Initial state or algorithms vary among categories, and are uniform within these categories.
2. **Individual**: Initial state or algorithms vary among all individuals, no agents are exactly the same.

Where categorical heterogeneity is used, empirical studies aiming to create a set of categories often carry out cluster analysis. This groups agents by sets of similar characteristics, with the assumption that these specific characteristics are a proxy to their behaviour (Bakker and van Doorn, 2009; Fernandez et al., 2005; Browder et al., 2004).

Within both ‘individual’ and ‘categorical’, heterogeneity can be classified further by whether it is ‘state-based’ or ‘algorithmic’. In state-based heterogeneity the algorithm or code under which they operate is the same, but differences in initial state variables or constants allow heterogeneity of behaviour. With algorithmic heterogeneity, the algorithm driving the decision making varies among agents. This is the strongest form of heterogeneity. It is analogous to humans using different procedures to carry out the same task. It is well known that humans possess this level of heterogeneity. For example, consider the range of methods used to solve a complex puzzle such as the Rubik’s cube. Algorithmic heterogeneity includes state-based heterogeneity because the state must necessarily be different among alternative algorithms. Different algorithms oper-
ate on state in a different manner. Even if state is uniform to begin with, the differences in processing of state during algorithm execution will mean different state will arise.

The BDI (Beliefs-Desires-Intentions) concept does not specifically address agent heterogeneity because it is concerned with the internal design of an agent - not the design of the multi-agent model as a whole. It is, however, certainly possible to construct a model with both individual, and algorithmic heterogeneity among BDI agents; even where the same BDI engine is being used. This is discussed in more detail in Chapter 4, and working examples are presented in Chapter 5.

## 2.10 Agent Interactions

Interactions are an important function of agent-based models. Without them an agent-based model would simply be a collection of unrelated autonomous objects, each occupying their own isolated world. Two types of interactions are modelled. Inter-agent interactions and agent-environment interactions. In some models, such as those of innovation diffusion, the only form of environment is the social network of other agents. In this case only agent-agent interactions are represented. In other models, the environment is a distinct entity, in which interactions between agents and their environment are specifically accounted for. Such models sometimes omit any direct agent-agent interaction, and instead use the agents’ ability to sense changes in the environment made by another agent’s actions as an indirect form of inter-agent interaction.

Where agent-agent interaction is modelled, a process of direct information transfer between agents must happen. To achieve this, concepts used within an individual agent model must be converted into a communicable form and read by receiving agents. It has implications for the design of the decision making model because certain types of information lend themselves to communication better than others. For example, information represented in symbolic form is easy to communicate, whereas parameters used in mathematical formulae do not have a natural or realistic means of inter-agent communication.

Three out of ten models reviewed used direct communication as the means for inter-agent interactions. The remainder—all described as representing social interactions—did so by using the ability of agents to sense the state of environmental objects (e.g.
land parcels) owned or influenced by other agents (Guzy et al., 2008).

2.11 Conclusion

A number of the models are described as representing the social aspect within the human-environment system. Among those models, some were found not to specifically represent inter-agent communication or behavioural heterogeneity among the agents—both of which are very important in characterising social systems.

Half of agent-based models reviewed used decision models based on processing a series of static rules as the top-level of decision making. The second most popular approach was the use of utility maximisation driven by mathematical optimisation. Both of these approaches tend to simplify and misrepresent human decision making.

Many of the models reviewed appeared to use simpler decision modelling techniques, either because of limited data availability or in a bid to aid understanding. In doing this there is a danger that the lack of detail and realism diminishes both the descriptive power and explanatory depth, making it difficult to generate any meaningful findings.

In order to address these issues it is suggested that more attention is paid to representing more human-like decision processes; making use of the cognitive faculties known to drive human decision making; with appreciation of the broad heterogeneity among decision makers.

As a final note, lack of model transparency appears to be a prevalent problem in applied agent-based modelling. Most of the works reviewed described the conceptual model, but did not go into enough detail to create an implementation. In some cases even the conceptual design is missing completely (Ligmann-Zielinska and Jankowski, 2007). This is a fundamental flaw in research, since the inability to reproduce the experiment makes it difficult for third-party researchers to test any insights found. ABMs have been rightfully criticised for this. It is hoped that these criticisms will encourage more modellers to release the blueprints (source or pseudo code) for their models.
Chapter 3

Human Decision Making: Underlying Theories and Concrete Models

Decision making has been the subject of significant research within the domains of economics, operations research and artificial intelligence. With its interdisciplinary nature it has received important contributions from many other research domains (Hansson, 1994). Areas such as psychology and neuroscience provide human-oriented, empirical knowledge, while mathematics and logic ensure the development of rigid, generalisable theories.

The goal of this chapter is to broadly introduce current theoretical understanding of human decision making. Key examples of human decision making models and synthesis techniques relevant to this research are provided. The final outcome of this review will be to propose a suitable method for modelling human decision making in applied ABMs, which ties into accepted theory of human decision making and has proved its applicability in the modelling domain.

3.1 What is Human Decision Making?

Human decision making is a mental process which leads to selection of a choice among a number of options. It involves first searching for and identifying the available options, then selecting a choice based on various criteria or preference. Finally, the selec-
tion usually results in the decision maker either taking action or updating their beliefs (Simon, 1993). Despite the straight-forward definition, human decision making is a non-trivial and difficult to model process. This is because of the complexity of our environment, coupled the complexity and limitations of the human mind.

According to Bratman et al. (1988), decision makers are resource bounded in terms of:

- **Time:** Constant changes in the environment mean that decisions almost always have a deadline.
- **Cognitive Ability:** The speed and volume of information processing; reliability and capacity of stored memory; and general intelligence.
- **Knowledge:** For many complex human decisions, access to all relevant information is often limited.

### 3.1.1 The Decision Environment

Human decision making environments are difficult because they are usually:

- **Dynamic:** In a constant state of change.
- **Partially Observable:** The current state of the environment cannot be fully known.
- **Uncertain:** Future states or outcomes cannot be predicted.
- **Continuous:** Time and space varies on a continuous analogue scale, rather than discrete steps.
- **Multi-agent:** Attention must be paid to other agents within the environment in the form of social interaction and anticipation of behaviour.

The dynamic nature of our environment inevitably leads to time constraints on decisions. This means there is limited time to search for knowledge/alternatives and to carry out cognitive processing. Our environment’s changing and partially observable nature means that human decision makers must constantly learn and revise their knowledge so that decisions are not poorly informed. Delaying decisions until the last minute is sometimes necessary to ensure we are acting on the most up-to-date information available.
3.1.2 Uncertainty and Risk

Making decisions in an uncertain environment inevitably leads to an element of risk (Hansson, 2007). This is because, if the assumptions under which the decision were made turn out to be false, then the results could turn out to be less favourable than expected. As a result we all employ some level of aversion to risk. Casual observation of our population demonstrates this. For example, people wear seat-belts to reduce risk of injury in a crash, or avoid harmful habits like smoking to reduce risk of contracting disease later in life.

3.1.3 Emotions

Often cited as a source of irrationality, emotions have been shown to affect human decision making. A large number of studies on the effects of emotions on decision making use a uni-dimensional measure of emotion (from positive to negative). For example, a decision maker in a positive mood will tend to search for more new alternatives, whereas a decision maker in a negative mood will tend to focus more on the attribute details of fewer alternatives (Mellers et al., 1998).

Other studies into emotions use more complex dimensions to measure emotions. In addition, some emotions are described as domain specific and cannot easily be integrated with other measures of emotion.

3.2 Theories of Human Decision Making

Within human decision making theory the notion of classical rationality and whether it can really be attained by human decision makers is often central to debate (Stanovich and West, 2000). It can be divided into two areas of thought: (1) the classical, decision theoretic perspective; and (2) the alternative, bounded rationality perspective.

Before discussing specific theories applied to human decision making, it is important to establish that some theories presented here may be more relevant to human decision making, than others. In certain areas the relevance a theory has in a human context can be an important subject of debate, for example utility theory.
An important distinction to make when examining theoretical works is their purpose. Some theories describe things from a ‘normative’ perspective (how things should be done), and others describe things from a ‘descriptive’ perspective (how things are done in reality). For example, a normative theory may dictate that a rational agent will take a specific decision because it maximises profit (what should be done). A descriptive theory, on the other hand may dictate that an agent will take a sub-optimal decision because the best decision was too hard to find (what is done in reality). As the goal of the thesis is descriptive modelling of human decision makers, theories from a descriptive perspective have much more relevance.

### 3.2.1 Decision Theory

Decision theory initially aimed at taking a completely objective view of decision making in order to formalise it. At first sight, the goal of ‘decision theory’ appears to meet the objective of the literature search. It aims to describe everything about how humans make decisions. Unfortunately, decision theory is not as all encompassing as that. It is mainly concerned with how we make a goal directed selection among a set of options. It does little to describe how the options are generated or even how the goals initially came about. However, since selection among options is really the core of decision making, it makes sense to focus on decision theory first.

A central concept in decision theory is that of rationality. A rational decision maker is one which selects the best option out of the options available. The term ‘best’ here is taken to mean the option which generates the most favourable outcome for the decision maker. In this respect decision theory is often regarded as normative, i.e. rational agents are following what should be the best course of action (Dastani et al., 2005).

So how can an agent make judgements between options? There are two high-level approaches:

The first uses relations among the options. Relations are often used by humans, particularly in informal contexts. For example: “a was better than b”. Applying numerical values to options implicitly allows the use of relations. However, if preferences are strictly represented as relations within a decision maker, then it may prove difficult to accurately convert them to quantitative form.
If all preferences can be reduced to a single numerical value representing overall utility (usefulness) it greatly reduces the complexity of choosing between options. Instead of having to work out problems using relations (such as $a > c, b < c$ implies $a$ is best), utilities can be applied, so that the option selected is simply that with the highest value of utility. For example, given options a, b and c with respective utility values of 5, 2 and 4, option a is the most desirable because it has highest utility value.

Within decision theory there are a number of mathematical techniques which can be applied to yield optimal decisions. These include decision matrices and mathematical programming. Decision theory also deals with decision making under uncertainty. Normally, the ‘expected utility’ of an option under consideration is calculated by combining actual utility and probability of success in the following way (Hansson, 1994):

\[
\text{Expected Utility} = \text{Utility} \times \text{Probability}
\]

Where a decision option has multiple outcomes then:

\[
\text{Expected Utility} = \sum_{i=1}^{n} \text{Utility}_i \times \text{Probability}_i
\]

Where $n$ is the number of outcomes.

### 3.2.1.1 Decision Strategies

In the absence of uncertainty, there are two basic decision strategies which can be adopted:

- **Optimising**: Finding all possible alternatives and selecting the one which will achieve the maximum level of pay-off (or utility).
- **Satisficing**: Deciding on the first option which achieves a minimum threshold level of pay-off. Note that the threshold level must be initially chosen by the decision maker.

When considering a number of uncertain options there are two basic approaches to optimising:
• **Maximax**: “Maximise the maximums:” select the alternative which has the highest of the maximum possible pay-offs. This is a strategy used by the optimist, and is based on the hope that the selected alternative will be close to the maximum possible pay-off.

• **Maximin**: “Maximise the minimums:” select the alternative which has the highest of the minimum possible pay-offs. This is a pessimist’s strategy and is a good way of dealing with risk because it ensures that the worst case scenario is as favourable as possible.

These approaches could also be used in conjunction with a satisficing strategy. For example, where a choice is made if its minimum possible pay-off is above a chosen threshold.

### 3.2.1.2 Applicability to Human Decision Making

Decision theory is generally regarded as a normative theory of decision making. It describes how the ‘correct’ decision can be made. However, in studies comparing human decisions to the norm (i.e. the decision theoretic point of view) it is often found that human decision makers do not perform with ‘perfect rationality’. The following explanations for the gap between classical rational norms and real human decision making were proposed by Chater et al. (2003):

• Performance errors
• Computational limitations
• Differences in understanding between experimenter and subject
• Effects of educational background and cognitive ability

However, with the consistent failures of decision theory to predict human decision making behaviour, these explanations based on errors or poor performance of humans looked weak as an explanation. It indicated that perhaps the theory itself was inadequate.
3.2.2 Bounded Rationality

Initially proposed by (Simon, 1957), bounded rationality was an alternative perspective on decision making to the traditional decision theoretic view. Its rise in popularity since then, is partly because it offered an explanation of the gap between human decision making, and the expected norm. Instead of being perfectly rational, decision makers could be regarded as rational with respect to their environment (information, cognitive resources and time available). Out of this concept came the term ‘ecological rationality’ (Gigerenzer and Selten, 2001). A heuristic is ecologically rational if it is perfectly adapted to its environment. Or in another way of putting it, the level to which a heuristic suits its environment, defines how ecologically rational it is.

So how would a boundedly rational agent be implemented? If decision theory is taken as a starting point, a key criticism is that an exhaustive search for alternatives may not be possible. To address this problem the decision maker can attribute a cost to the information search. The decision maker would then cease the search for alternatives as soon as the cost of searching outweigh the benefits of a good decision (Anderson and Milson, 1989). This is called ‘optimisation under constraints’. Although it seems sensible, optimisation under constraints may also suffer the same problem as unbounded rationality in that calculation of search costs and benefits can demand significant resources (Gigerenzer and Todd, 2000).

Similar to optimisation under constraints, ‘satisficing’ is an alternative approach to bounded rationality which enables the search for alternatives to cease early (Simon, 1957). However, instead of using cost of search as the stopping rule, the decision maker only looks at the benefit of each option and stops the search when it has reached a chosen threshold. Although this strategy may be more efficient than optimisation under constraints, it still involves the calculation of benefit (or utilities) in order that options may be compared, and requires the decision maker to decide on a suitable threshold before commencing the search. As a result the satisficing strategy may not be adequate for describing decision making behaviour in highly dynamic situations with stringent demands on time and resources.

Bounded rationality, as proposed by Gigerenzer and Selten (2001) is a set of decision making tools readily accessible to the decision maker including:

---

1 A Heuristic is defined as simple and efficient decision making rule
1. **Search rules** describing information to use and procedures to follow during the search.

2. **Stopping rules** informing the decision maker when to cease the search.

3. **Decision rules** used to quickly make a choice among the alternatives gathered. These do not involve utilities or optimisation.

In order to adapt to the environment, these rules (or heuristics) need not be static, but may be updated at any time in light of new information by means of reinforcement learning.

Sticking to these simple rules is said to provide the advantages that decision makers can use information readily available in the environment, and can easily deal with situations involving multiple goals, unlike optimisation. Additionally, from a modeller’s perspective, the fewer number of parameters demanded of these simple strategies help to avoid the risk of over-fitting, as can happen with complex optimisation models.

### 3.3 Model Implementation Techniques and Architectures

At this point the review moves from the purely theoretical perspective on decision making, to a more applied modelling perspective. The implementation of decision makers inside computational models involves a number of choices, borrowing techniques from the large body of knowledge within Computer Science and Artificial Intelligence.

#### 3.3.1 Agency and the AI Perspective

In order to provide a concrete implementation of any decision maker, the decision algorithm is not enough. It is necessary to specify the environment and how the decision maker operates within it. Artificial Intelligence (AI) uses the term ‘agent’ to represent an object capable of intelligent autonomous behaviour within its environment.

When constructing an agent it is important to consider its operating environment because this can have implications for the design of the agent architecture and the decision making model within. Different environments can be characterised by a number of features. The following list describes the top-level characteristics which can be used
to classify them:

1. **Partially or fully observable**: whether the agent is able to sense all of its environment.
2. **Deterministic or stochastic**: whether (from an agent’s point of view) the environment is predictable.
3. **Episodic or sequential**: whether a decision is affected by, or affects the future.
4. **Static or dynamic**: whether the environment changes without action by the agent.
5. **Discrete or continuous**: whether spatial and temporal characteristics of the environment change in discrete steps.
6. **Single or multi-agent**: whether the environment contains one or many agents.

The most difficult environment from an agent design perspective is one which is partially observable, stochastic, sequential, dynamic, continuous and multi-agent. This is exactly the kind of environment human decision makers are faced with. In modelling human-environment systems it is often necessary to equip the agent to handle environments with these properties.

When modelling with human agents it is necessary to provide them with a form of ‘intelligence’ which allows them to successfully operate within their environment. It is not easy to find an all-encompassing definition for intelligence, but (Wooldridge and Jennings, 1995) summarises three capabilities which autonomous agents are expected to have:

1. **Reactive**: Able to produce a timely response to changes in their environment.
2. **Proactive**: Able to take the initiative. They can act independently of stimulus to achieve their goals.
3. **Social ability**: Able to interact with other agents in order to help achieve their own goals.

The following is a summary of some general AI techniques which can be used to implement these characteristics in artificial agents:

**Goals and Utility Functions**: Reflexive and model-based agents are coded with rules which are designed to satisfy its objective (or goal). The problem is that these architectures are not very general. As soon as an agent’s goals need to be changed, it is
necessary to change the rules used to generate actions from perception. Goal-based agents solve this problem by representing goals explicitly. It works by maintaining a database of rules, known to achieve certain goal states. When a goal is selected, the specific rules known to achieve the goal state are applied.

Goal-based agents add an element of flexibility in the agent design, but they may not be suited to problems in which there may be a number of solutions. For this, agents need a way to decide which rule results in the most beneficial environmental state. Utility functions serve exactly this purpose. They map a world state to a utility value (utility here means usefulness). A complication associated with using utility functions in a partially observable environment is that the agent must be equipped to handle both utility and uncertainty, to provide a measure of expected utility.

**Layered Architectures / Subsumption:** This is a reactive type architecture which is constructed from layers of behaviours. The higher level behaviours (for example, ‘move’) depend on lower level behaviours (for example, ‘take step’). With this architecture it is possible to generate complex behaviour from simple rules. It solves the problem of model complexity encountered with many of the symbolic approaches.

**Problem Solving** agents are used where simple goal directed behaviour is not adequate in solving the complex problems involved. Problems where a particular sequence of actions is required to find a solution. Conventional planning/problem solving systems work by searching the problem space for a viable solution. Techniques such as heuristic analysis and bidirectional search help to reduce the size of the search problem. Genetic algorithms provide an alternative approach to exploring the search space. In planning systems, plans can be derived in a forward (progressive) sequence or reverse (regressive) sequence, the most efficient of which depends on the particular application.

**Constraint Satisfaction:** This is another method for exploring the search space, this time specifying the problem as a set of constraints. Linear programming is an example of a commonly used constraint satisfaction algorithm. It works by finding the solution to multiple simultaneous linear equations.

**Game Theory** is used in multi-agent environments to reason about the possible action of other agents. In a competitive game, agents’ goals are to maximise their own utility by minimising their opponent’s. In a cooperative game, agents maximise their utility
by maximising that of other agents. Game theory is primarily a normative approach, and as such may not provide a realistic representation of human interaction.

**Knowledge Based Systems:** These provide a means by which to represent more complex information, and to use it to derive new knowledge or solve problems. Knowledge can be represented using first order logic, predicate logics or ontologies (Russell and Norvig, 2003). Such systems can be useful in modelling human decision making because they can equip an agent with the ability to reason about its environment, and learn via logical inference.

**Machine Learning:** These systems equip agents with learning capability. ‘Learning’ here is taken to mean adaptation of behaviour based on perception of past state. There are three categories of machine learning:

- **Supervised:** Learning by referring to examples of inputs and the expected corresponding outputs. This is also known as inductive learning.
- **Reinforcement:** Learning from past good, or bad experiences. It can be used to discover how an environment behaves with respect to given actions.
- **Unsupervised:** Learning to recognise distinct patterns of input where no expected output, or training data are available.

Although these techniques are normally used in isolation, they can be combined together to achieve the desired requirements within an agent model. While this is appropriate for normative/engineering applications, the lack of a concrete, unifying theory behind this approach may make it less appropriate for descriptive modelling of human decision makers. Instead of combining these techniques arbitrarily, a high level theory of human decision making is required. These techniques can then be used to provide a concrete implementation, consistent with the underlying human decision making theory.

### 3.4 The BDI Model of Decision Making

Beliefs-Desires-Intentions is a theoretically-based approach to modelling the human decision maker, based on folk psychology (Norling et al., 2001). It relies on being able to examine our own thoughts (or ‘thinking about how we think’). The popular-
ity of this approach comes from its intuitive representation of our view of cognition. It is easy to relate to. The implications are that models using agent architectures designed from this perspective should be more transparent, allowing for easier analysis and communication of results.

Initially proposed by psychologist Michael Bratman, the Belief Desires Intentions (BDI) model of practical reasoning is based around the notion of three mental attitudes (Bratman, 1987; Rao and Georgeff, 1991):

**Beliefs** represent the agent’s knowledge. They hold its view of the world state, the state of itself, and that of other agents. Because of the limited visibility of the environment, the state of beliefs at any instant may not be consistent with the actual world state. A BDI agent must periodically revise its beliefs to ensure they remain as up-to-date as possible.

**Desires** (or motives) represent the motivational state of the agent. They are goals which if satisfied are believed to achieve a desirable state. Desires usually have preconditions or a context, which specify the state of affairs necessary before they can become intentions. For example the desire to ‘make a cup of tea’ would normally require the agent not to currently possess a cup of tea.

**Intentions** are desires which have been committed to (or whose execution is imminent). Carrying out or ‘executing’ a desire is usually done by making use of known plans and possibly raising new intentions. Crucial to intentions is the idea that they have been committed to. Once an intention is being pursued, no other desires or plans which are inconsistent with the intention may be considered (Cohen and Levesque, 1990).

This theory is believed to provide a good approximation of the human reasoning process, but according to Norling et al. (2001) there is: “much scope for refinement”. In particular, some argue that the various concepts in BDI require more rigorous formalism.

An approach following the BDI philosophy is sometimes criticised, because it may be the case that the mind generates some thoughts which cannot be consciously detected. An example of this might be where a skill is so ‘automatic’ that the decision maker can make a snap decision without being consciously aware of the reason for it. However, although the theory is based on introspection, it does not limit methods of behaviour
elicitation to only those based on introspection. Any behaviour elicitation technique may be used in conjunction with introspective approaches to extract the more subtle aspects of our reasoning.
Chapter 4

Methodology: Building an Agent Model from Decision Narratives

4.1 Introduction

This chapter describes a process by which real human decision making behaviour is recorded and encoded into an artificial agent - the core methodology behind this research.

As described in a similar study, investigating the decision making of players of the Quake computer game, some applications require “...psychologically plausible behaviour (that is, where the observed behaviours are generated by an underlying process that captures human reasoning as closely as possible).” Norling (2008) p1.

This is the goal of this technique. To construct a plausible artificial model of human decision making, usable in a simulated agent-based model. This has wide ranging applications in the field of agent-based modelling research, as discussed in Chapter 2.

4.2 Methodology Overview

The methodology can be considered as an empirical technique, for the elicitation of human decision making behaviour and encoding in an algorithmically executable form.
Figure 4.1 shows the overall procedure adopted in the methodology, illustrating how data collected from each stage is used in subsequent stages. The broken arrows indicate where recorded and simulated data are compared during validation. Each stage is described in more detail below.

The goal of the initial behaviour elicitation stage is to draw out the subject’s decision making behaviour. During this stage the experiment subject is asked to carry out decision tasks within a simulated environment. This environment is designed to mimic as closely as possible, the situations the decision makers are typically faced with in reality. During this phase the subject generates two types of data: (1) A sequence of actions used to manipulate the simulated environment and (2) Narratives describing the strategies adopted and the reasoning behind their adoption. Both of these are recorded during the behaviour elicitation stage, and then used as input to subsequent stages.

The following behaviour schematisation stage involves analysis of the narrative data to construct a high-level description of the subject’s decision making strategy. This is called a behaviour schema. The behaviour schema structures the narratives into a set of desires and preconditions expressed in the same language used in the original narratives. This is to ensure minimal deviation from the original meaning intended.

From the behaviour schema, each of the behaviours and their preconditions can be directly coded into BDI desires and activation preconditions. This is the core task
involved in the next stage: **behaviour encoding**. During behaviour encoding, actions used by the subject to satisfy each intention are used to form the plans of the artificial agent. The process of encoding agent behaviour also involves a certain amount of work to ground the high level constructs used by human decision makers to the low-level detail within the model itself.

The final stage of the methodology involves **validation**. This step is crucial to get right in the methodology. Without proper validation, it is impossible to gauge whether the original goal of creating an artificial representation of the subject’s decision making has been achieved. Many options may be used in validation, but in general it involves comparison of the actions and narratives produced by the subject with those generated by its artificial agent representation.

The remainder of this chapter discusses each of the four stages in more detail.

### 4.3 Behaviour Elicitation

The purpose of this phase is to gather the data necessary to reconstruct an artificial representation of the decision maker. The methodology chosen is designed to extract a true and representative as possible profile of the decision maker’s behaviour, while at the same time minimising the introduction of errors or bias into the measured behaviours.

As described in Chapter 3 the choice of BDI for modelling decision makers provides the advantage that introspective human reasoning has a fairly direct route to translation into the beliefs-desires-intentions framework. The choice of BDI here provides freedom to use more naturalistic or ‘qualitative’ methods for behaviour elicitation. With this freedom it is possible to apply techniques in which domain experts express their knowledge in its most natural and intuitive form - using their spoken language. This reduces the cognitive burden on the subject during behaviour elicitation. It allows attention to be focused on the task environment, encouraging the most natural and representative behaviour to be expressed (Van Geenen and Witteman, 2006).

The behaviour elicitation stage broadly involves two phases. (1) A participatory simulation session with the experiment subject, involving recording of decision narratives


and actions. (2) Follow up interviews to clarify the decision model created from data gathered in the first phase. A key design choice in this methodology is to ensure that minimum possible researcher intervention takes place before the initial participatory simulation session. The reason for this is to reduce the possibility of a researcher’s influence creating any bias or error in the final decision model.

4.3.1 Elicitation Methods Adopted

From the broad literature on knowledge elicitation and (CTA) cognitive task analysis comes a vast toolbox of techniques for eliciting behaviour and knowledge in different forms (Liao, 2005). However, it should be noted that comparatively little work has been done to evaluate or compare alternative methods for knowledge elicitation. Selection among them is generally based on the researcher’s judgement rather than the results of objective studies (Holsapple et al., 2008).

A large number of examples of methods applied in this area are reviewed by Wei and Salvendy (2004), citing specific examples of where they were used and the strengths and weaknesses of each technique. For clarity, Wei organises these techniques into four general families based on their level of formality and the mechanism used for analysis:

1. **Observations and Interviews.** These less formal methods are deemed to be useful and a natural way to define the domain, but often have the problem of generating data which is difficult to use and interpret in a decision modelling context. Examples include: unstructured or structured interview, and direct observation.

2. **Process Tracing.** Subjects perform a specific task, while providing a running commentary explaining their decisions and actions. Data generated from these methods are usually in narrative form which in itself can be difficult to examine and interpret. In addition, data sets generated are often large, making them difficult to manage. Process tracing methods, however have the advantage of being fairly straight forward to carry out. Examples include: cognitive walk-through and protocol analysis.

3. **Conceptual Techniques.** Explicitly structure domain concepts and their inter-relations, usually in diagrammatic form. These less direct methods of CTA in-
volve less introspection and verbalisation on the part of the subject, and tend to produce data in a form which is easier to aggregate and interpret. On the down-side, data gathered in these methods focus on the conceptual elements of a domain, at the expense of procedural (or task performance) elements. Examples include: conceptual graph analysis, diagramming, rating/ranking-paired comparison, repertory grid and sensori-motor process chart.

4. **Formal Models.** Uses preconceived formal models and maps human behaviour onto them, with the assumption that these models approximate the underlying processes at work in human cognition. They suffer from the obvious dependence on the correctness of the underlying model, but can be a fast and inexpensive way to formalise a task domain. Examples include: ACT Model, Human Processor Model and GOMS.

In general, there is no right or wrong technique to use, but the effectiveness of a technique depends on the research domain and its goals.

Hoffman (2008) cites the ‘multimethod’ approach, asserting that it is widely accepted as being beneficial to knowledge elicitation. Researchers will “...strategically craft a program of KE [knowledge elicitation methods] to fit a particular project.” (p. 484) rather than sticking to one specific methodology.

A combination of two knowledge elicitation methods are used in this methodology. The primary method applied is protocol analysis or ‘think aloud’ task performance (Crutcher, 1994). This is specifically applied in a participatory simulation context, meaning that a decision making task is performed by the subject using a simulated representation of the task environment. While the participatory simulation is taking place the subject ‘thinks aloud’ by verbalising the actions being performed and the reasoning behind them.

The second method applied is semi structured interview (Lindlof and Taylor, 2002). It is used as a follow up to the initial participatory simulation session to further clarify the initial narrative data provided. It may be useful to carry out these interviews after the process of behaviour schematisation or even after behaviour encoding since both of these steps often bring out further issues which may be missed by the researcher during informal analysis of the raw narrative data.

More detail on each of these methods and how they are applied in the methodology
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4.3.2 Participatory Simulation

Simulation models provide a ‘virtual laboratory’ for conducting experiments, where doing them in a real environment may not be practical or possible (Winsberg, 2003). In comparison with real laboratories or studies in the field, they offer a much greater array of tools and techniques to support research. For example, time can be varied, compressed, paused or reversed. Space can be abstracted and represented at multiple scales. They also allow repetition of multiple experiments under exactly the same environmental conditions. In addition, a rich array of simulation outputs can be measured, some of which may be impossible to measure in reality.

Using participatory simulation to elicit decision making behaviour provides researchers with a high degree of control over the decision environment faced by the subject. Multiple scenarios can be generated and tested to glean a range of decision behaviours (Ramanath and Gilbert, 2004). Taking farming as an example, measuring farmer response to changes in climate would require years of ongoing research if decision making was sampled using real farming situations. In addition, the climate change scenario presented to the subjects would be imposed by nature, rather than researchers. It would be unlikely to test a wide enough range of climate change scenarios to be useful to policy makers.

4.3.2.1 Participatory Simulation in Other research

From the literature, the terms ‘participatory simulation’ and ‘role-playing games’ are used interchangeably and take on different meanings. Where used, these terms generally imply the research is focused around ensuring stakeholders are directly involved in some aspect of the research. Exactly which aspects of the research and the nature of involvement can vary significantly.

In its least computer-oriented form, stakeholders are typically asked to take part in an interactive board game with other stakeholders. A representation of their environment (usually a map of their local area) is used along with other props as the basis for interaction. These sessions are designed to elicit some aspect of stakeholder opinion,
social behaviour or decision making (Afonso and Prada, 2008; Barnaud et al., 2008). These types of research are usually either referred to as ‘participatory research’ or ‘role-playing games’ (RPG).

While the data gathered from these RPG workshops need not be used in any simulation-based research, they often are (Downing et al., 2001; Becu et al., 2008; Stoorvogel et al., 2004). In these types of projects stakeholders can help inform model scenarios and define the decision making environment. They can also provide an indirect source of behaviour elicitation for the purposes of developing agent-based simulations.

Other ‘participatory simulation’ studies use the subjects to directly elicit behaviour for the design of agent-based simulations, but contrary to the intuitive meaning of ‘participatory simulation’ they are not actually involved in participating with the simulation platform itself. The use of the term ‘role-playing’ is not really appropriate for these kinds of research projects. The word ‘participation’ refers to subjects helping researchers to build decision making profiles, using various elicitation methods. The decision-making data gathered is then used to develop artificial agents for a simulation platform.

The final, and probably most intuitive definition for ‘participatory simulation’ is where subjects are directly participating with the simulation model. In these studies, participants are asked to use a simulation platform which presents users with a simulated environment. Tasks or scenarios are presented to the subject in order to provoke an opinion or behaviour which is then measured as part of the research. This type of experimentation can equally be called ‘participatory-simulation’ or use of ‘role-playing games’. This is the way in which participatory simulation is used in this project and will be the intended meaning when referring to ‘participatory simulation’ within the context of this project.

4.3.2.2 The underlying simulation platform

The methodology presented here assumes the pre-existence of a representative simulation platform of the decision environment under research. If that does not exist it will need to be created. The procedure behind this process is only discussed briefly here, but is an important consideration. Detailed description and specific examples of the process of development of simulation environments can be found in chapters 5 and 6.
During development of the simulation platform it is often necessary to use the knowledge of subject matter experts to gather domain information. It is suggested that this process of development should be kept independent of the experiment subjects. Although it will usually involve experts from the domain, it would be unsound to use persons involved in the design or construction of the simulation environment as subjects of behaviour elicitation for an agent-based model. This is because any involvement in the development process gives the subject clues to the workings of the underlying model, and may cause elicited behaviour to represent behaviour with respect to a known representation of the system, rather than an expectation of the real system.

Where domain experts are used in simulation development, it may be difficult for a few experts to cover all possible scenarios involved in the task. In addition, during participatory simulation, the subjects involved may encounter scenarios that the experts have missed. This certainly is a hazard within the method. If attention is given to making the system as close to reality as possible then many scenarios may emerge from the system, without needing to be specifically expressed. In any event, where serious omissions are found it may be necessary to re-visit the model development phase using feedback from previous experiment subjects or information from further domain experts.

4.3.2.3 Method for its Application

In preparation for participatory simulations, first a training session is held to allow participants to become familiar with the simulation platform. During this session the functionality available in the user interface will be described and a basic model scenario is run. The scenario used should allow the subject to make use of the range of interface features and functions, whilst minimising exposure to any realistic decision making scenarios. The aim is to encourage familiarity with the interface, while minimising exposure to the workings of any underlying models so that the first realistic decision making happens only during the subsequent experiments. Typical techniques for doing this would be to set scenario variables to be constant, or completely random, so that no obvious patterns may be observed.

When subjects are familiar with how the interface operates the participatory simulation experiment can begin. The subjects will be asked to use the participatory simulation
platform with driving variables\(^1\) set to present realistic decision making scenarios. The nature and range of individual scenarios presented depends on the research question, but in general it will be desirable to run a number of scenarios to be used for behaviour elicitation, and at least one scenario to be used during validation. In order to maintain consistency all scenarios may be placed into a single multi-scenario simulation run. This prevents interruption of the experiment and prevents the subject gaining the expectation that a change in scenario is occurring. In many cases this is reflective of reality, in which future decision making scenarios are unpredictable and may happen at any time.

As well as using chosen scenario variables, it is possible to use random generator functions to vary driving variables according to a particular frequency and distribution. This has the advantage of reducing the predictability of scenarios, and if used on a number of driving variables will allow a range of scenario setups to be tested. Where a Monte Carlo approach is used to generate driving variables it is important to start from a known random seed, while using a pseudo-random function to generate the numbers. This ensures the state of driving variables can be re-created for simulation re-runs or experimentation with other subjects.

Within this methodology the participatory simulation phase is a non-iterative one. This means that once all participatory experiments have taken place they will not be revisited, unless it involves testing an alternative set of decision scenarios. The reason for this is that if a subject is presented with the same scenario again they can use knowledge learned from the previous simulation to make decisions, rather than relying purely on their original decision making knowledge.

### 4.3.3 ‘Think Aloud’ Decision Making

During participatory simulation, the behaviour of subjects is elicited by asking them to ‘think aloud’. This technique is also known as *protocol analysis*. A study by Van Geenen and Witteman (2006) established that protocol analysis was successful in not only extracting an expert’s knowledge but also as a way of understanding its structure. However, it suffers the problem that implicit knowledge is often not to be

\(^1\)The term ‘driving variables’ here refers to initial input values which govern the behaviour of the simulation model.
verbalised during the decision task. For this reason a multi-method approach, also including semi-structured follow-up interviews, is necessary.

Within the methodology, protocol analysis is the first elicitation technique to be used. It is done without prompting to avoid interference with the task at hand. It also prevents the researcher inadvertently providing clues or hints as to what the scenario involves. If probing (interviews) are left until after the participatory simulation then the decisions have already been made, so it’s impossible for researchers’ questions to affect the actual decisions made during the experiment.

During application of protocol analysis, three possible methods are given to participants for recording decision narratives. (1) Handwriting, (2) Typing and (3) Speaking into a dictaphone. The third option would be the least intrusive method, but in practice participants may feel uncomfortable with using dictaphones, and may prefer to opt for the typed/handwritten options. It is suggested that if the dictaphone option is chosen, that booths are provided to allow the experiment to take place in a private setting.

A problem with using protocol analysis is that it may be difficult to gather enough information for a complete model of the decision maker during the course of a single experiment (Hoffman, 2008). This could be combated by running a number of participatory simulation experiments until the number of new behaviours exhibited by the subject drops significantly. If this is not practical then further information must be gathered during subsequent interviews—an idea that is discussed later in the chapter.

### 4.3.4 Narratives as the Core Format

The output from protocol analysis is a series of decision justification narratives. These narratives form the basis upon which the agent model will eventually be built. Knowledge expressed in this form is natural to everyone and can be very expressive. It allows researchers to record a decision maker’s behaviour on tape, with the minimum of interruption or interference. Narratives also have the advantage that they are easily understood by both researchers and subjects, unlike symbolic logic, program code or other abstractions. They can be used at all stages in the research to provide a transparent form of validation, usable by all parties involved.

The expressive advantage of using narratives also raises some issues. Human language
contains ambiguities and omissions. In normal conversation we are usually able to resolve these issues by using the context and our knowledge of the world to derive the complete picture. However, some of this contextual sense may be lost when a researcher reads over the narratives later in the lab. Alongside this issue, there is also the problem that some of a domain expert’s knowledge is so second nature that it is processed implicitly, with little or no conscious thought made (Crandall, 1989). Within a narrative it will simply be abstracted away or appear as an assumption.

With these cases of ambiguities, omissions or implicit knowledge, further steps need to be taken to resolve them and extract the level of detail necessary to encode the knowledge as a functional agent. Two things are used in the methodology to deal with these issues (1) follow up interviews to provide clarification where necessary and (2) the actions made by the subject are recorded alongside the narratives. When observed during a re-run of the simulation, these actions often provide the context necessary to disambiguate the meaning.

4.3.5 Procedural Options for Participatory Simulation

An important issue to be considered for the narrative elicitation process, is the order in which each elicitation step should take place. Regardless of the order, the following must happen:

- The subject takes part in a participatory simulation.
- The subject provides narratives describing/justifying their behaviour during the simulation.
- A researcher probes the subject to ensure adequate information has been provided.
When order is taken into consideration there are a number of possible options. The list below presents plausible sequences for the narrative elicitation process.

During participatory simulation:

1. Subject provides no behavioural justification, focusing on the simulation task;
2. Subject provides behavioural justification, but with no interviewer present;
3. Subject is probed for behavioural justification by interviewer at key points.

During re-run of recorded simulation:

4. Subject provides behavioural justification, but with no interviewer present;
5. Subject is probed for behavioural justification by interviewer at key points.

The problem with providing justification during the simulation run is that attention is focused on providing reasons for the behaviour, rather than concentrating on the task at hand. The addition of an interviewer to this process is likely to make it even more distracting and exacerbate this problem. This is a problem for options (2) and (3).

The problem with retrieving justification during the re-run is that subjects may have forgotten the initial motivation for their actions, and the justifications may have been made up to suit the actions observed (post-justification of behaviour). A problem for options (4) and (5).

Initially, allowing the subject to freely provide justification without prompting is likely to result in the least biased/tainted results - good for option (2). But then the action of providing that justification may cause over-analysis of the task at hand, resulting in unrealistic behaviour.

The advantage of using an interviewer is that it allows a focus on areas where clarification is missing. This is good for (3) and (5). However, the use of an interviewer to probe for extra information should be used sparingly as interviewer prompts may lead to suggestions that the behaviour should have more motivating factors even if it originally did not. Because of the danger of probing affecting the subject’s behaviour, sitting through the participatory simulation in order to prompt should be avoided, thus option (3) is not desirable.
The advantage with leaving interviews to post-simulation is that it allows the researcher to analyse the data in order to pick out areas in need of clarification. In this case, only those areas in need of clarification would be in danger of post justification. It also gives the researcher the option of keeping the original data set (unaffected by the interviewer) separate from the enriched (and possibly over-justified) data set resulting from interviewer probing. If the interviewer is a domain expert there is another potential source of bias, where the interviewer attempts to map the interviewee’s responses onto their own domain knowledge. In these cases the interviewer should take care to avoid introducing bias.

If option (1) is chosen for the simulation run, then option (4) followed by option (5) would ensure that the subject has the opportunity to give behavioural justification without probing and possible over-justification.

Because it is easier to explain your actions while you are doing them, option (2) followed by option (5) is preferred over options (1) followed by (4) then (5). This has the added advantage that the subject need only run through the entire simulation twice, rather than three times: Once during the participatory simulation and a second time during the follow-up clarification interview.

A further advantage of option (5) is that the simulation need not be run at original speed. It can be ‘fast-forwarded’ where no significant decision making was being made, and slowed down/paused at important decision points.

If option (2) is being used, it is important to ensure the subject is fully aware of exactly what is required in a behaviour justification. It requires both the behaviour (what is happening), and a justification (why it is happening). Both these elements need to be present in each justification for it to be usable in construction of a BDI agent.

A similar study by Norling (2006) involved examining the decision making behaviour of players in a real-time action game. Because of the fast-paced nature of the task, it would be difficult for the subject to provide justification during task performance. The researcher proposed that the events should be recorded first, followed by post-simulation interviews to extract the subject’s decision making behaviour. The research demonstrated that the choice of whether decisions should be narrated during, or after the simulation is partly dependent on the nature of the task or simulation environment itself.
Compared to the decision environment in Norling’s study, farmer decision making is not quite as fast paced. The simulation environment has been designed as a single player, turn-based game. This means that the user controls the progression of time during the simulation, and as a result is allowed as much time as necessary to make decisions. This also leaves ample room for providing decision justifications. Because farming decisions are made over much larger time-scales than those involved in action games, the ability of the user to control the forward progression of time is unlikely to affect the realism of the decision environment. In reality a farmer would have hours, or sometimes even days to make decisions.

The problem of introspection during the task causing over analysis and a possible bias in the result is present whether the decision justifications are taken during the simulation or after (during a re-run). It is proposed that the pressure of having an interviewer present may be more likely to exacerbate this problem rather than reduce it. For this reason decision justifications are taken during task performance, without an interviewer present. This is thought to be most likely to produce ‘natural behaviour’. As discussed previously this methodology is not appropriate in all applications and is particularly unsuited to fast-paced real-time simulations.

In this methodology post interview analysis may still be an important part of the process, because it allows any ambiguities or omissions to be clarified and added. When using this technique great care needs to be taken to avoid any additional ‘embellishment’ to decision justifications.

4.3.6 Semi-structured Follow-up Interviews

Semi-structured interviews are used to clarify narratives given during the participatory simulation stage. In addition, they can be used to find new narratives for any actions made which did not have an obvious justification given in the first instance.

The questions to be asked during the interviews are mainly found during behaviour encoding and agent validation, when narratives are analysed and the resulting schema and models are scrutinised. The greater the quantity and better the quality of narrative data gathered initially, the less important this phase will be. If perfect, fully detailed narratives were generated during the participatory simulation then it would be possible
to create a fully functional agent during later stages of narrative analysis without any further data required. In reality however, this is unlikely to happen.

The first instance in which a need for further interview becomes apparent is in the first part of agent encoding, in which the narratives are converted to a high-level descriptive agent model (schematisation). During this step each distinct behaviour (or motive) is extracted, along with the preconditions necessary for its execution, and the beliefs called upon. Where there are ambiguities in the preconditions, or preconditions are missing all together, then these must be clarified at the interview stage. Again, where references are made to beliefs with ambiguous meaning, or where levels or quantities of belief variables are unclear, further information must be gathered during interview.

During the second stage of behaviour encoding, the high-level agent description must be grounded within the simulation platform itself. During this step the distinct behaviours extrapolated during the previous step will be associated with actions generated by the agent during the simulation. Where actions are observed to have taken place, but no motive is present to explain these actions, new motives must be found, by again revisiting the interview stage. In addition, the process of grounding the agent model is likely to raise more issues of ambiguity or omission in agent beliefs and preconditions. These must again be resolved via semi-structured interviews.

Finally, during validation of the working agent model, the original subject may be presented with narratives generated by the artificial agent, during a test simulation. As a form of verification, the original subject will be asked how closely the narratives match their behaviour. The actions generated by the agent will also be compared with the narratives they correspond to. The original subject will be given the opportunity to comment on how likely it is that the given motives would generate the observed actions.

Even with good initial narrative data, the application of interviews, throughout the agent development process helps to ensure that the final agent matches the original agent as closely as possible. Figure 4.2 illustrates how information from each of the stages in agent development is used to feed back into further interviews to generate a more detailed and clarified narrative basis. A similar iterative methodology was applied in studies by Becu et al. (2008) and Guyot and Drogoul (2005).
4.4 Encoding Behaviour into an Agent Model

This section describes the process by which the data collected during the behaviour elicitation stage is used to develop an artificial agent model. It involves two sub-stages. First the narrative data are used to create a high-level agent model (or schema). The second sub-stage then uses this agent schema, along with action data recorded during the simulation to create a detailed agent model capable of execution within the simulation environment.

4.4.1 Motivational Objects: Generalising Desires and Actions

A distinction is made between the term ‘desire’ in BDI, and the similar term ‘motive’ used within this methodology. The distinction concerns the way in which low-level actions are represented. In BDI, actions are contained within plans and not directly included in the BDI reasoning process. Actions are a consequence of the planning process, and are not directly accessible before a desire has become an intention. The problem found with using this representation in practice, was that the line between what constitutes an ‘action’ and a ‘desire’ is not clear cut. Depending on the context in which a motive is expressed, it may be categorised as either an action or a desire. Consider the following narrative snippets:
1. “increasing herd size to meet increasing milk demand”
2. “buying cows to increase herd size”
3. “saving money to buy cows”

Taking 1 in isolation, the desire is meeting increasing milk demand, and the action is to increase herd size. Taking 2 in isolation the desire is to increase herd size, and the action to fulfil this is buying cows. Between the two snippets increasing herd size can be either a desire or an action. Similarly considering 2 and 3, buying cows can again be considered either a desire or an action. Taking all three snippets together, everything can be considered a desire with the exception of saving money. This is because nothing has been said about how saving money is achieved within the narrative, so it cannot be broken down into further sub-motives. It must be an ‘action’ supported by the interface between the agent reasoning algorithm and its environment. Its realisation is external to the reasoning process.

When analysing a full narrative, those motives which are not specified in terms of lower-level sub-motives must be considered as actions which have a direct effect on the agent’s environment. If these are not considered actions then it will not be possible for the output from agent reasoning to affect the environment. The problem with BDI, is that it requires a line to be drawn somewhere between objects which are desires and those which are actions, keeping desires and actions distinct, and treating them differently. Any objects identified as actions may not be included in the core reasoning process, and are simply executed when carrying out a plan. It is not possible to reason about them in the same way as desires. For example, assessing available options with respect to the current context, or excluding those which are inconsistent with current intentions.

The modified BDI implementation used within this methodology unifies desires, plans and actions into a single ‘motive’ object. A motive may represent a high-level goal such as ‘seek profit’ or a low level action such as ‘apply fertiliser’. If a motive is a high-level desire then a plan is used to satisfy the motive when it becomes an intention. The result of executing a plan is to raise one or more further motives. If a low-level action motive becomes an intention, it simply results in that action being taken. An action motive can be regarded as being atomic, since it results in no further motives being raised. Regardless of the level of abstraction of motivational objects, they all share the common property that they are designed to achieve some state of affairs.
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Whether this will be satisfied directly, or via further planning is transparent within the reasoning process.

### 4.4.2 Finding BDI Components within Narratives

The core of the encoding methodology is a system for translation of natural language decision making narratives into a BDI agent model. In a similar manner to a study by Norling (2006), the technique works by analysing sentence components to glean the constructs used in the Beliefs-Desires-Intentions model. As discussed in Chapter 3, the necessary components to construct a BDI model are:

1. **Beliefs**: An agent’s knowledge about itself and the state of the environment. They include any pieces of information used by the subject to make their decision. The majority of beliefs are expressed within preconditions and usually relate to an aspect of the state of the environment. They are not limited to this however. Beliefs may be other internal information objects including knowledge, memories or predictions. Beliefs associated with learned knowledge are arguably the hardest component to extract. This is because expert knowledge is often vast and learned over many years of being exposed to a wide range of different scenarios. Extracting it all would require exposing the subject to a range of scenarios in which each piece of knowledge is required at least once.

2. **Motives** (or desires): A set of motives which allow the agent to achieve a desirable state of affairs. These include high-level goals realised by executing plans, and low-level atomic motives which directly result in action. What they all have in common is that they are statements which describe what the subject wanted, needed or planned to do.

3. **Preconditions**: This is state of affairs perceived by the subject which caused or influenced a motive to become an intention. Often it is simply an environmental condition such as ‘good weather’ or ‘low milk prices’. Sometimes, it is a higher level motive, or a combination of a higher level motive and an environmental condition. Where the same motive is expressed multiple times with different preconditions, the *OR* keyword was used to indicate that either set of preconditions may cause the motive to be executed (become an intention). When multiple factors are involved in activating a motive, a conjunction of the motives involved is expressed with the *AND* keyword.
In order to find these constructs within decision narratives a system is required for analysis of narratives which pulls out these components with the minimum room for interpretation or ambiguity.

Before its possible to do this, sentences of a particular structure, containing adequate decision making information are required. Two high-level elements are needed: (1) The intention of the decision, i.e. what it is designed to achieve; and (2) The reason that the decision was taken. For example, considering the sentence:

“The current land use is no longer making a profit, so I’m switching to an alternative use.”

It contains both an intention (to switch to alternative use) and its justification (current use no longer making profit). The reasoning behind the decision provides the beliefs that were called upon to make the decision, as well as the conditions that were met in order for the decision to be committed to. The intention of the decision provides the motivation behind the decision and sometimes provides hints as to the actions that were taken to fulfill the intention. If the actions are not present in the narrative it is possible to find the actions that were taken, by making reference to the actions recorded during participatory simulation. However, if multiple decisions were taken at one instance it may be difficult to find any certainty as to which actions correspond to which decision. As discussed in the previous section, follow-up interviews may be necessary to resolve these kinds of issues.

The overall process of converting narratives into an agent model is broken down into three sub-steps. First the narratives are read over to map words, phrases, and sentences to each of the three BDI components. Next each distinct motive or ‘desire’ highlighted is added to the agent schema table. Each precondition associated with the motivation is then added to the table, with specific reference to the beliefs used to evaluate the precondition. Finally, in the third step, the high level behaviours and their preconditions are encoded in programmatic form. This process also requires the implementation of a body of support code required to allow a mapping from high level beliefs and motives to low level data representations and action plans. This is also known as grounding the agent model.
4.4.3 Initial Interpretation of Narratives

The first stage of the process involves going through all narratives from participatory simulations and highlighting which words, phrases or sentences constitute desires, which ones are preconditions, and finally which words or phrases refer to beliefs. Table 4.1 shows an example of a set of narratives extracted from a single experiment scenario, along with the BDI components highlighted accordingly.

Some beliefs which are called upon may not be explicitly stated in the narrative, but are implicit in the reasoning. I.e. it would be impossible to carry out such reasoning without such a belief. For example, considering the narrative:

“I’ve decided to switch all my land cells to use A because B seemed to be failing.”

It would imply that the subject maintains the belief that some of the land cells are assigned to use B, even though it is never explicitly stated in the narrative. An unambiguous version of the narrative in respect of land use assignment might be:

“I’ve decided to switch all my land cells from use B to use A because B seemed to be failing”.

Once BDI components have been highlighted, a second sweep over the narratives is done to identify beliefs and motives which are distinct, and those which are duplicates of each other. As an example, the motive expressed in step eight (Table 4.1) is the same as the first motive expressed in step two.

If a motive is repeated (or the same motive is expressed in different language) it is given the same numeric identifier as the first occurrence of that motive. Sometimes several motives may be expressed in the same sentence. For example, when the following sentence actually contains two motives:

“Reverse to see if the difference is better overall.”,

The first motive is to ‘reverse’ (meaning revert to the original strategy), and the second (sub motive) is to ‘see if the difference is better overall’. In this case the two motives should be given separate numbers since each of the sub motives may be mentioned in different contexts later in the narrative. For example, ‘see if the difference is better
overall’ may be executed because of a higher level motive to ‘try a new strategy’. Where motives are nested like this, the precondition for a sub-level motive is simply to satisfy the higher level one.

A similar process takes place for numbering distinct beliefs which were used. Any duplicates are assigned the same numeric identifier so that they can be easily identified and grouped together in the next stage: creating the agent schema.

The next section presents the precise notation and formatting rules used to interpret narratives.

4.4.4 Notation and Formatting for Narrative Interpretations

The BDI components within each narrative are highlighted according to the following colour scheme:

- Green represents motives.
- Blue represents beliefs.
- Red represents preconditions.

The exact format used for highlighting the narratives depends on the narrative type. If the subject motive is based on a precondition, such as the following:

“This is a motive caused by this precondition which is based on this belief.”

The resulting annotation and highlighting would be:

[m1] This is a motive caused by (this precondition based on this belief [b1]).

Where m1 is the unique identifier for the subject motive and b1 is the unique identifier for the belief used in the precondition.

If the subject motive is based on another motive, such as the following:

“This is a motive caused by this higher level motive.”

Then the resulting annotation and highlighting would be:

[m1] This is a motive caused by ([m2] this higher level motive).
Chapter 4. Methodology: Building an Agent Model from Decision Narratives

Key: Motives, Beliefs (Preconditions)

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[1] Give each area a surrounding area to thrive in. [2] Chose pattern to make sure no cells bordering the dark were also dark</td>
</tr>
<tr>
<td>2</td>
<td>[3] Same strategy as (got good results[1]). [4] Extend to mark cells dark where the growth is least so shade in all four corner cells (A1, A5, E1, E5)</td>
</tr>
<tr>
<td>3</td>
<td>Forgot to do the last instruction so ditto!</td>
</tr>
<tr>
<td>4</td>
<td>(Widespread gain[2] but still low[1].) (Spreading land use over wide area not working) so switching to strategy where I will have [5] one area of dark and one of light. Colour cells a1, a2, b1, b2 dark and the rest light</td>
</tr>
<tr>
<td>6</td>
<td>(Too intensive[3]) so will [8] reduce to dark areas of only two blocks. Keep A1, A2 and E4 and E5</td>
</tr>
<tr>
<td>7</td>
<td>(Lowest areas[1] still furthest from dark areas) so will [9] try a spread of dark areas across all corners leaving middle free. Change D1, E1 and A5, B5 to dark as well</td>
</tr>
<tr>
<td>8</td>
<td>(Positive result[2]) so will [3] maintain strategy for one more go</td>
</tr>
<tr>
<td>9</td>
<td>(Still good[1]) although will [10] test by colouring the lowest square dark(E2).</td>
</tr>
<tr>
<td>10</td>
<td>[11] Reverse to [12] see if the difference is better overall.</td>
</tr>
<tr>
<td>12</td>
<td>(Loss[2] in areas where I have had dark patches in for a while[4]) and so will [14] remove corner pieces.</td>
</tr>
<tr>
<td>14</td>
<td>same reason as last round</td>
</tr>
<tr>
<td>15</td>
<td>(Hit plateau[1,2]) so [17] new strategy based on idea to [16] keep areas homogenous. Will [18] try random pattern of blobs (three of four cells of dark cells).</td>
</tr>
<tr>
<td>21</td>
<td>Same as reason before</td>
</tr>
<tr>
<td>28</td>
<td>(Fluctuates at level[1] lower than strategy before using the corners as bases of three dark cells). [11] Return to this strategy. (dark cells (A1,2,4,5 B1,5,D1,5,E1,2,4,5)</td>
</tr>
</tbody>
</table>

Table 4.1: Interpreted narratives
Chapter 4. Methodology: Building an Agent Model from Decision Narratives

The general rules for formatting are:

- Motives (including their identifier) are highlighted green.
- Motive identifiers are a numeric value with the ‘m’ prefix.
- Motive identifiers appear in square brackets before the motive they refer to.
- Preconditions are highlighted in red formatting and enclosed by normal brackets also highlighted in red.
- Beliefs and motives used as preconditions are highlighted as beliefs (blue) and motives (green), overriding the red highlighting of the precondition. Red brackets allow preconditions to be identified even if all highlighting of the textual content is not red.
- Beliefs (including their identifier) are highlighted in blue.
- Belief identifiers are a numeric value with the ‘b’ prefix.
- Belief identifiers are placed immediately after the belief they refer to in square brackets.
- When highlighting a belief only the belief object itself should be highlighted, and not any accompanying qualifiers. For example in a precondition making reference to ‘low prices’ only the word ‘prices’ should be highlighted.

4.4.5 Creating the Agent Schema

The purpose of this stage is to create a high level descriptive model using only the subject narratives. No knowledge of how the environment works should be required for this stage, but it can be useful to re-play the subject’s behaviour to resolve any ambiguous language. The constructs in this description do not need to refer directly to environmental objects. Here, only the concepts and structures referred to in the narrative language are being used.

The general structure of the agent schema consists of a list of agent motives, and with each motive a set of preconditions which are satisfied before the motive is committed to. Each precondition is based on the state of a set of beliefs. The beliefs used in each precondition must belong to the fixed set of agent beliefs, originally extracted from within the narratives.

In order to make the process of constructing the preconditions easier it is useful to write
## Chapter 4. Methodology: Building an Agent Model from Decision Narratives

### Motive

<table>
<thead>
<tr>
<th>Motive</th>
<th>Precondition(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Give each area a surrounding area to thrive in</td>
<td>New strategy at start of game</td>
</tr>
<tr>
<td>2. Chose pattern to make sure no cells bordering the dark were also dark</td>
<td>To satisfy 1</td>
</tr>
<tr>
<td>3. Stick with same strategy</td>
<td>Revenue Level $\geq$ Good OR Revenue Change $\geq$ Positive (Good)</td>
</tr>
<tr>
<td>4. Extend to mark cells dark where the growth is least. (Extending same land use over wider area)</td>
<td>To satisfy 3</td>
</tr>
<tr>
<td>5. One area of dark and one of light.</td>
<td>Revenue Change $&gt; 0$ on $&gt; 50%$ of cells AND Overall Revenue Level $\leq$ Low</td>
</tr>
<tr>
<td>6. Make opposing corner dark</td>
<td>Revenue Level $\leq$ Low (in areas furthest away from dark land use)</td>
</tr>
<tr>
<td>7. Going for intensive block</td>
<td>To satisfy 6</td>
</tr>
<tr>
<td>8. Reduce to dark areas of only two blocks</td>
<td>Use intensity $&gt; High$</td>
</tr>
<tr>
<td>9. Try a spread of dark areas across all corners leaving middle free</td>
<td>Revenue Level $\leq$ Low (in areas furthest away from dark land use)</td>
</tr>
<tr>
<td>10. Test by colouring the lowest square dark</td>
<td>Revenue Level $\geq$ Good OR Revenue Change $= 0$</td>
</tr>
<tr>
<td>11. Reverse (put back)</td>
<td>To satisfy 12 OR Revenue Change $&lt; 0$ OR (Revenue Change $&gt; 0$ AND Avg Revenue Level over time $\leq$ Low)</td>
</tr>
<tr>
<td>12. See if the difference is better overall</td>
<td>None, new strategy</td>
</tr>
<tr>
<td>13. Corresponding changes in other corners</td>
<td>To satisfy 11</td>
</tr>
<tr>
<td>14. Will remove corner pieces</td>
<td>Revenue Change $&lt; 0$ in areas (groups of cells) where Length of time on land use (dark) $\geq$ a while</td>
</tr>
<tr>
<td>15. Stick to strategy of blocks of dark areas</td>
<td>Revenue Change $\leq$ very poor</td>
</tr>
<tr>
<td>16. Homogeneity (keep areas homogeneous)</td>
<td>To satisfy 15</td>
</tr>
<tr>
<td>17. New Strategy</td>
<td>Revenue Level $\geq$ High AND Revenue Change $&gt; 0$</td>
</tr>
<tr>
<td>18. Try random pattern of blobs</td>
<td>To satisfy 16</td>
</tr>
<tr>
<td>19. Chequerboard</td>
<td>To satisfy 11</td>
</tr>
</tbody>
</table>

Table 4.2: High-level agent schema
down the belief set in an ordered list, before construction of the agent schema. The list should express the belief in its simplest and most concise form. This will ensure the preconditions are as clear as possible, using the same terminology for the same beliefs, even if the original narrative used different language. The list below shows the set of beliefs (along with their unique identifiers) extracted from the narrative data in Table 4.1.

- b1. Revenue Level by Cell
- b2. Overall Revenue Level
- b3. Revenue Level by Area
- b4. Areas (groups of cells)
- b5. Average revenue level for a ’period’ of time
- b6. Revenue Change
- b7. Use Intensity
- b8. Length of Time on Same Use by Cell

The list is derived from explicitly and implicitly expressed beliefs, but may not be exhaustive. Subsequent grounding of the model may reveal more implicit beliefs used, which may not have been obvious during the initial interpretation of the narrative content.

For clarity, the agent schema is best presented as a table with two columns. The first column contains all distinct numbered motives. Where the same motives are used and expressed in different terms, it is important to include all forms in which the motive is expressed, to ensure meaning is not lost. These alternative expressions for a behaviour may then be used by the artificial agent when expressing its reasoning.

The second column contains all preconditions which were satisfied before the motive was activated. Where a motive was expressed more than once, with different preconditions used, the OR keyword should be used to separate each precondition set. This indicates that either of the preconditions may have caused the motive to be activated. Preconditions should only be expressed in terms of the beliefs in the list created previously and no additional expressions should be used. Where subjective quantitative levels are described in the narrative, the quantifier should be expressed in exactly the same language which was used. For example “revenue was high” would be expressed as revenue \( \geq \) ‘high’.
Where a motive is executed, directly as a result of commitment to a higher-level motive, the precondition should simply refer to the higher level as its trigger. In the example below the phrase “To satisfy x” is used, to indicate the motive is executed in order to satisfy x (the higher level motive triggering it).

Table 4.2 shows an example agent schema, generated from the narratives in Table 4.1. The following section presents the precise formatting rules used to construct the agent schema.

From this table, each of the motives may be directly converted into BDI ‘desire’ objects. The preconditions in the second field, may again be directly coded into the BDI model as conditions which must be satisfied before the motive may become an intention. Finally, the belief set used within the schema provides the BDI agent’s database of beliefs. During execution of the agent model, these beliefs are periodically revised, and subsequently called upon to facilitate BDI reasoning.

### 4.4.6 Notation and Formatting for the Agent Schemata

The schema is presented as a two-column table, with the left-hand column representing motives and the right-hand column containing the preconditions associated with the motive in the same row.

If building an agent schema for the following interpreted narratives:

[m1] The first motive caused by (this first belief [b1] and this second belief [b2])
[m2] The second motive, using the value 2 and due to (this third belief [b3])
[m2] The second motive, using the value 5 because of ([m1] the first motive)
[m2] Value 1 used with the same second motive

The resulting agent schema is presented in Table 4.3.

These are the general rules for formatting:

- Motives in the left column must appear exactly as they did in the original narrative and be preceded by their unique identifier.
- If the same motive is expressed elsewhere in the narrative, but using different terminology, it must also be added to the cell representing that motive.
Chapter 4. Methodology: Building an Agent Model from Decision Narratives

<table>
<thead>
<tr>
<th>Motive</th>
<th>Precondition(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>m1. The first motive</td>
<td>this first belief [b1] AND this second belief [b2]</td>
</tr>
<tr>
<td>m2. The second motive, using the value x</td>
<td>(this third belief [b3]</td>
</tr>
<tr>
<td>m2. Value x used with the same second motive</td>
<td>OR</td>
</tr>
<tr>
<td></td>
<td>(to satisfy [m1]</td>
</tr>
<tr>
<td></td>
<td>OR</td>
</tr>
<tr>
<td></td>
<td>(none stated</td>
</tr>
</tbody>
</table>

Table 4.3: Example schema

- All preconditions which caused a motive to be executed must be placed in the right-hand column of the row representing that motive.
- If a motive was executed because of more than one precondition being true the AND keyword should be used to separate them.
- If the same motive appears in the narrative, but is caused by a different precondition, the precondition should be added to the same cell as the original precondition(s) but separated using the OR keyword.
- If a motive is executed because of a higher-level motive, then the phrase ‘to satisfy [m#]’ should be used as the precondition, where m# is the unique identifier for the higher level motive.
- If a motive is executed but no precondition is given then the precondition should be listed as ‘none stated’.
- Where a chosen value or quantity is used in a motive, the exact value should be replaced with a suitable parameter symbol (x for example). Where a motive has parameters associated with it, any preconditions causing the motive should also record the value of the parameter when the precondition held.
- Within the preconditions, beliefs are highlighted blue and motive identifiers are highlighted green.

4.4.7 Grounding the Agent Model

In order that the agent model may be executed in a simulated environment, these high level narrative descriptions need to be converted into algorithmic form. Any abstract
concepts used need to be fully specified to a level of detail accepted by the model environment. For example, the concept of ‘an area of land’ would need to be specified in code as a contiguous group of land cells. This is possibly the most hazard-prone process in the methodology, because it is where most interpretation is required. It is where meaning must be pulled out of the narrative snippets to allow the concepts to match up to the simulated world’s objects. As witnessed in similar studies, grounding the agent can be a significantly laborious process (Norling, 2008).

4.5 Agent Behaviour Validation

As with any modelling project, this part of the methodology is probably the most important, as it determines how closely the model represents its subject. With a good validation process it will be possible to gauge with confidence that the model is behaving in a similar manner as the original decision maker.

So what method(s) can and should be used to validate the agent model? In this methodology three key approaches can be used:

1. Comparison of the real and simulated agents’ actions and their effects on the simulated environment;
2. Comparison of the narratives generated by the real and simulated agents in similar scenarios;
3. Judgement by the original subject on how closely the agent’s actions, narratives and effect on the environment represents his/her own behaviour and the result of it.

All three forms of validation will provide some measure of the success of the final model. At a minimum both the first and second methods of validation should take place. Using only method 1, it may be possible to show that the real and artificial agents generate the same actions and effects on the environment, but this does not necessarily mean that the same reasoning process is taking place. If it can not be shown that the same reasoning is occurring, then it is difficult to convince anyone that the artificial agent will behave correctly in new, un-tested scenarios. If however only the second method of validation is used then although we will be convinced that the agents are reasoning in a similar manner, the output and effects of their reasoning will
not be guaranteed to be the same.

The third method is not a necessity, but it should be encouraged, since the original subject has the best knowledge of his/her own behaviour. It should be used with caution however, since the subject’s judgement may be prone to bias from pre-conceptions on machine intelligence, amongst other things.

4.5.1 Validation of Actions and Their Effects

In its least direct form, this validation process involves the use of carefully chosen metrics to measure the state of the simulation environment at any given instant. For example, a land-use scenario might use a simple measure of the proportion of land assigned to a particular use. Under similar scenario situations it would be expected that the real agent and its artificial counter-part would be making use of the land in similar proportions.

Using these kind of metrics can be useful because they are able to provide a clear quantitative measure of similarity. They allow statistical methods to be used to objectively measure correlation between the results of real and artificially generated behaviour.

As well as comparing the results of an agent’s actions on the environment, it is also possible to compare the actions themselves. In a sense, this gives a more direct comparison between agents, but can suffer from the problem that they are more difficult to analyse quantitatively. The rationale behind validating with respect to actions over just simply validating with respect to their effects, is that it is often possible to achieve the same state of affairs in the environment through a different set of actions. It could be argued that even if two agents bring about the same state of affairs in the environment, their actions and method for bringing about that state of affairs may differ.

Statistically comparing the actions generated by agents may be done by measuring the frequency of occurrence of each type of action. Actions themselves often have parameters associated with them. For example, the action to buy fertiliser has a quantity associated with it. When comparing actions these parameters should also be accounted for.
4.5.2 Validation of Reasoning via Narratives

It could be argued that even validating against the actions produced by agents is not enough to get a good measure of how closely an agent matches the subject it represents. The most convincing validation of agent models would show that the reasoning process which brings about these actions matches the reasoning of the original subject. The problem however, is that this is probably the most difficult thing to do objectively. This is the reason that a lot of agent-based models are often only validated with respect to their effect on the environment, and at most the actions they generate.

The narratives produced by the subject during the experiment are probably as close as possible to accessing the raw reasoning process of the agent, without physically measuring brain activity itself. Because of the way in which a BDI model represents the reasoning process internally, it is possible to provide the model with the ability to produce narratives during execution. By looking at the behaviours expressed under similar scenario conditions and the reasoning given, it is possible to judge how closely the reasoning of the agent and subject matches. If behaviours are grouped into a finite set of categories, it is possible to measure the frequency and type of behaviours to provide some objective statistics. In addition, where the reasoning behind decisions is expressed, it is possible to check that the same beliefs are called upon in making the decisions, and that the quantities expressed are the same or similar.

4.5.3 Simulated Scenarios used in Validation

An important consideration during the validation process is the scenarios used to validate the models. If agents were validated using the same simulation scenarios as were used to build them, then it could be argued that the agent is only valid and usable under these particular scenarios. This is even more pertinent in the process of building models of human reasoning, because many new and different behaviours may be used when the scenario changes. For the purposes of validation, it will be necessary to choose at least one scenario in which the data gathered is not used in building the agent, but instead kept aside for validation. If the scenarios used to capture behaviour for agent development are wide enough in scope, they should be able to capture the behaviour exhibited in the validation scenario.
4.6 Conclusion

Within the chapter a methodology for empirical modelling of human decision making behaviour was described. The methodology consists of four stages:

1. Elicitation of human decision making behaviour in the form of narratives and recorded actions, by carrying out participatory simulations of a range of decision making scenarios.
2. Interpretation of the recorded narratives to construct a high level schema, suitable for encoding as a BDI agent.
3. Encoding of the agent schema as an executable BDI agent, making use of recorded actions and follow-up interviews to ensure the semantics of the narratives are correctly represented within the agent model.
4. Validation of the agent model, by carrying out simulation runs on scenarios not used in agent development, and comparing recorded and simulated behaviour.

The following chapter (number 5) presents a case study in which the methodology was applied to an abstract land-use scenario, using university students as experiment subjects. Chapter 6 then assesses the feasibility of up-scaling this methodology to a realistic domain. Participatory simulation experiments within a dairy farming scenario are carried out - using dairy farmers as experiment subjects.
Chapter 5

Case Study 1: Human Decision Making in an Abstract Scenario

5.1 Introduction and Background

This chapter details an initial set of experiments designed to elicit human decision making behaviour using the methodology outlined in Chapter 4. For this first case study it was decided that the decision making scenario should be simple and easy to understand, rather than being a realistic reflection of agricultural decision making. The idea was to emulate some basic properties of land-use decision making, where expected revenue from the land resource is uncertain and varies in both a spatial and temporal dimension. The aim of these experiments was twofold. The primary objective was to attempt to recreate as far as possible, the decision making behaviour of the experiment subjects. The secondary objective was to assess the methodology and examine where further improvements could be made.

A similar experiment was conducted by Evans et al. (2006), in which human subjects were asked to assign abstract uses to a 5x5 grid of cells. The subjects would then receive real monetary rewards based on revenues earned from each cell. During the experiment the revenue received on each cell depended only on the use applied to the cell. The performance of the subjects was then compared with the performance of a utility maximising agent. The conclusion was that in this particular scenario, the behaviour of a utility maximising agent is a poor approximation of human behaviour.
The setup for Evans’ experiment involved the subject assigning one of two possible uses to each of the 25 cells, in a series of consecutive rounds. In each round the subject would receive information on the revenue gained in each cell. But crucially, they were given no information as to what the revenue would have been if the cell was assigned to the alternative use for that round. On an abstract level, this reproduced a similar property in a real land use system. Land users do not know exactly what the outcome of their land use decisions will be until they have committed to them. They may only use indicators to make judgements, such as past performance, commodity prices or the profitability of neighbouring land.

In order to ensure the subjects had incentive to make good decisions, the amount they were paid to take part in the experiment was directly proportional to the artificial revenue they received in the simulation. This had the effect of introducing risk, because if they performed very poorly in the experiments they were not adequately rewarded for the time forfeited to take part.

The conclusions made from Evans’ study however, may have been slightly misguided. The problem with the set up was that the view of the state of the environment provided to the subjects was not the same as the view provided to the utility maximising agent. While the utility maximising agent was provided with full information on the current round’s revenues for both possible land uses, the human subjects were only given access to the revenue which resulted in the last round’s land use selection. This meant that decision making was trivial for the agent—it simply chose the cells known to provide the maximal payoff. The human subjects on the other hand, needed to make predictions based on actual revenues earned in the previous round. Making accurate predictions in this scenario would be difficult even for a utility maximising agent, and would require the agent to apply sub-optimal land use patterns in order to establish which uses for each cell would result in the highest possible revenue.

However the experiment is set-up, it is important that both the human subjects and the artificial agent have exactly the same view of the simulated environment. If this is not the case then it is difficult to draw meaningful conclusions from the experiment, since the decision making task presented to the agents is not the same as as the task carried out by the subjects.

The case study presented here applied a similar abstract land use scenario, using a
similar arrangement for participatory simulation experiments, but with the crucial ex-
ception that both agents and subjects were presented with exactly the same view of the
environment. Unlike the study by Evans et al. (2006), the aim is to construct agents
which reproduce the behaviour of the original subjects as far as possible.

5.2 The Simulation Platform

The simulation platform consists of a simulated abstract land-use environment and a
graphical user interface (GUI) that allows subjects to make land use decisions and
receive feedback on them. Appendix A shows the documentation packaged with the
simulation program, which provides instructions to those taking part in the experiment.

The simulation takes place in a cellular environment consisting of a 5x5 grid of cells.
Land use is abstract and can be one of two possibilities blue or green. The goal of
the subjects is to select a land use for each of the cells in each simulation round, such
that profit is maximised. At the end of each round subjects receive information on (1)
the revenue gained on each of their cells, and (2) the overall revenue received for that
round.

The graphical user interface (Figure 5.1) presented to experiment subjects is divided
into an upper section for data input, and a lower section for output from the model. The
input section contains a 5x5 cellular region for making land use selections. Clicking
the mouse over a cell toggles the assigned land use between the two options available.
Next to the land use selector a text area is provided for expressing decision making
rationale. If changes are made to the land use in any round, without any explanation
given the interface will prompt subjects to provide some reasoning.

Beneath the input components in the lower section, the interface shows a 5x5 revenue
grid. It displays the revenue received from each land cell on the previous round. The
cells are shaded according to revenue received, from red for low profit to green for
high profit. The exact profit values are also displayed numerically, followed by a + or -
sign indicating whether profit for the last round was higher or lower than the previous
round. To the right of the revenue grid some other statistics are shown, including the
total revenue received in the previous round and the total revenue received in the game
so far. It also displays a graph showing change in revenue over time, to allow subjects
Case Study 1: Human Decision Making in an Abstract Scenario

Careful consideration had to be made when showing the cellular output. In early designs the revenue grid only displayed the revenue for each cell numerically. During testing it became evident that it was difficult to assess the revenue of cells relative to their neighbours to check for patterns of differing performance. For this reason, it was decided to also shade each cell according to the revenue value, on a sliding scale from red (for low revenue), through yellow (for average revenue), to green (for high revenue). As well as needing to know the total revenue, subjects also paid attention to the change in revenue for a particular cell from one round to the next. In order to allow subjects to keep track of which cells grew and which ones fell a + or - sign was added as a suffix to the numerical revenue value. Another option was to display change in revenue numerically, or by using a similar shading system, but it was decided that this would present too much information and may lead to confusion between absolute revenue amounts and revenue change.

In order to facilitate programming of the system, some external libraries were used. Most notable of which were JADEX (a BDI agents library) and the JFreeChart charting library.

Figure 5.1: Graphical user interface

to keep track of change in performance.
5.3 Initial Pilot Study

Before the main experiment was done, an initial pilot study was done to test the methodology to identify problems and to make improvements where ever possible. It involved using a single subject to extract decision narratives. These narratives were then examined, interpreted into an agent schema, encoded into a software agent and finally executed on the same simulation environment to compare the results.

5.3.1 Experimental Setup

The experimental design for the pilot study was similar to the setup used by Evans et al. (2006). The main difference being the experimental setup relating to the artificial agents. Data produced from the simulation with a human subject was used to compare the subject’s land use decisions with those produced by the artificial BDI agent. Unlike Evans’s experimental method the agents act with exactly the same view of the environment and model state as the human subjects were given. This ensures a fair comparison of human and agent decisions.

The following algorithm was used to calculate revenues for each land use:

Given the land use $L$ is applied to cell $i, j$ at time $t$, the revenue $R$ received is described in the equation below. It varies with respect to $P$, the price of products generated by each land use $L$ at time $t$; and $S$, the suitability of each land use $L$ at cell $i, j$.

$$R_{i,j,t} = P_{L,t} + S_{L,i,j}$$

for

$$i = 1, 2, ..., 5$$
$$j = 1, 2, ..., 5$$
$$t = 0, 1, ..., 39$$
$$L \in \{Blue, Green\}$$

In all experiments, both the subjects and artificial agents only receive access to the revenue received in the previous round. The price and suitability data have the purpose of creating spatial and temporal heterogeneity in revenue values, but are never
directly visible to the land user. Over time, a successful land user may start to derive the underlying spatial and temporal changes through careful observation of received revenue.

In the pilot experiment only the price of products from each land use was varied, while the suitability parameter was unused. This kept things simple so that problems with the methodology would be easier to identify. The prices varied linearly, with $P_{Blue}$ decreasing from 0.65 to 0.35 and $P_{Green}$ increasing from 0.35 to 0.65. Thus, they follow the trends described in the equations below, further depicted by the graph in Figure 5.2.

\[ P_{Blue,t} = \frac{-0.3t}{40} + 0.65 \]

\[ P_{Green,t} = \frac{0.3t}{40} + 0.35 \]

The land suitability parameter was set to 0 on all cells for both Blue and Green land uses, such that:

\[ S_{L,i,j} = 0 \quad \forall L, i, j \]

Figure 5.2: Price trends in blue vs green land uses

5.3.2 Narrative Interpretation

It should be noted that the methodology used to interpret the subject’s narratives during the pilot study was under development. The methodology presented in the main study
(later in this chapter) and also in Chapter 4 is an evolution of this one, and has some obvious differences.

The narratives provided by the subject involved in the pilot study are presented in Table 5.1. During the narrative interpretation process, the narrative script was read carefully and scanned for a set of unique desires (or strategies) expressed. The desires identified are listed below, headed by the unique three-character code used to uniquely identify them in future.

- **dNP**: Try completely new pattern - unrelated to last one, leads to: bPA - happens when uncertainty is very high, or desire for risk is very high (because of low satisfaction).
  
  Must select land use either:
  
  - Cell-by-cell: only random selection with either use equally probable.
  - Areas (triangle, square, circle).
  - Patterns (checkered, lines, crosses, fill).
  
  Within each of these there is a need to keep an eye on bLR (ratios) and bLD (distribution).

- **dTR**: Wait for trend, leads to bPT.

- **dCH**: Change to compare, (using bPT and bPC of each construct) leads to bPC.
  
  - Cell-by-cell: changing just use.
  
  - Areas: changing type, size, location, orientation and use.
  
  - Patterns: changing type, orientation, ratio of use, distribution, use.

- **dKP**: Keep land use, result of high bST also leads to bPT, but lack of bPC by this scheme leads to greater uncertainty bUC which in turn leads to lower bST.

- **dRT**: Return to previously known good arrangement.
### Step Narrative

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I wanted to know if a protective border would prove useful and profitable.</td>
</tr>
<tr>
<td>2</td>
<td>I’m happy with the results of the protective border but want to continue to change the land use to see if there is a larger profit to be made.</td>
</tr>
<tr>
<td>3</td>
<td>The land use of the border proved profitable in earlier trials, so wanted to see if it would increase the profit if the land use in the middle was changed.</td>
</tr>
<tr>
<td>4</td>
<td>This land use proved best last year. I repeated my choice to see if the trend would continue the following year.</td>
</tr>
<tr>
<td>5</td>
<td>This land use is proving best, I’ll continue because I feel confident about its use.</td>
</tr>
<tr>
<td>6</td>
<td>This land use is going down, only marginally but curiosity makes me want to experiment with a small area of different land use and see the results.</td>
</tr>
<tr>
<td>7</td>
<td>Disappointed with the results of the land use change. Will try another small area elsewhere.</td>
</tr>
<tr>
<td>8</td>
<td>Again disappointed with result. Try another area, keeping land use change areas small as they are not making as much as the blue land use.</td>
</tr>
<tr>
<td>9</td>
<td>Again, still not making as much as I could, even with randomised land use.</td>
</tr>
<tr>
<td>10</td>
<td>Coming to the conclusion that to make the best use of land and most profit I should run with the blue land use.</td>
</tr>
<tr>
<td>11-15</td>
<td>[none]</td>
</tr>
<tr>
<td>16</td>
<td>The value is going down marginally each year. Time to try out other land use, starting in small areas.</td>
</tr>
<tr>
<td>17</td>
<td>Trying out different areas of land use to see if profit will change.</td>
</tr>
<tr>
<td>18</td>
<td>Green land use is still proving that it is not as profitable as the blue land use. Even though the blue land use is decreasing in value each year it is still the best one to continue using.</td>
</tr>
<tr>
<td>19-20</td>
<td>[none]</td>
</tr>
<tr>
<td>21</td>
<td>Worryingly, the value of the blue land use has dropped by quite a bit. Feeling anxious so again try the strategy I previously used, changing small areas.</td>
</tr>
<tr>
<td>22</td>
<td>Green is now showing more profitable but being cautious, I only double its area and not risk changing a larger area just yet.</td>
</tr>
<tr>
<td>23</td>
<td>Again slowly adding more blue as it is proving to do well.</td>
</tr>
<tr>
<td>24</td>
<td>Green has proven to do better than the blue land use. I feel confident enough to change a larger area but keep a few blue squares to see their value. The blue squares I have chosen are opposites of each-other, one high right, one low left to get a better idea of any changes.</td>
</tr>
<tr>
<td>25</td>
<td>These 2 blue ‘control’ squares have shown that blue is the way to go this year.</td>
</tr>
<tr>
<td>26-34</td>
<td>[none]</td>
</tr>
<tr>
<td>35</td>
<td>Although I am making a good profit and it is increasing I introduce one square of a different land use to compare and make sure I am getting the best deal.</td>
</tr>
<tr>
<td>36</td>
<td>Obviously not. Change back.</td>
</tr>
<tr>
<td>37-40</td>
<td>[none]</td>
</tr>
</tbody>
</table>

**Table 5.1: Decision making narratives from the pilot study**
As well as scanning for unique desires expressed, all unique belief objects referred to within the narratives were identified and are listed below. Again, a unique identifier is used for unambiguous reference to specific beliefs in following work.

- **bST**: Satisfaction Level (1) very dissatisfied, (2) fairly dissatisfied, (3) neutral, (4) fairly satisfied, (5) very satisfied.
- **bRS**: Risk taking (lower satisfaction leads to more risk - because less to lose). bRS has an impact on parameters used in dCH.
- **bU**: Uncertainty (more leads to lower bST)
  - **A**: Absolute profits (no expectation of actual profits).
  - **T**: Uncertainty of trend.
  - **C**: Uncertainty of relative advantage between each land use.
- **bP**: Profits
  - **A**: Absolute profits of(individual cells or patterns), leads to bPT and bPC.
  - **B**: The best profits a cell has received.
  - **W**: the worst profits a cell of that land use has received.
  - **T**: Difference between profits when keeping same pattern between rounds.
  - **E**: Expectation of profits - given bPA, bUA, bPT, bUT.
  - **C**: Difference between profits resulting in land use changes.
- **bL**: Land Use
  - **C**: Individual Cells (location, use).
  - **A**: Contiguous movable areas (location, shape, size, orientation, use).
  - **P**: Complete pattern schemes (orientation, use).
  - **R**: Belief of land use ratios (total of one vs total of another).
  - **D**: Distribution - level of concentration of land use in different zones.

Once the distinct beliefs and desires used had been defined, the narratives were then re-read and an interpretation was created. The purpose of this step was to provide an intermediate representation expressed in the English language, but expressed in such a way as to facilitate a more direct route to encoding as a BDI agent. Table 5.2 below shows the interpretation of the narratives in table 5.1.

<table>
<thead>
<tr>
<th>Key:</th>
<th>Desires, Beliefs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step</td>
<td>Interpretation</td>
</tr>
<tr>
<td>1</td>
<td>Working blind, tries a pattern [dPT, bST=3]</td>
</tr>
<tr>
<td>2</td>
<td>Looking at first profit fairly satisfied [bST=4] but wants to wait for trend [dTR] because bUT is low.</td>
</tr>
</tbody>
</table>
Chapter 5. Case Study 1: Human Decision Making in an Abstract Scenario

Changing land use to compare one with the other [dCH], leads to gain of bPC, using pattern of (fill) which has bLR(green) of zero because bPA(blue) > bPA(green).

Did well, so bPA(blue) is high, but bUT(blue) also high - sticking to dTR will lower this.

Again high so bST is high. means low desire to fiddle with it. Also, continuing with dTR means that bUT(blue) is getting higher.

Changing land use to compare one with the other [dCH], this is because bUC is high as lots of time has passed since last dCH course of action. leads to gain of bPC, chosen area bLA (ratio = small because bPA(green) is low)

Results were bad, so changing land use again, [dCH] changed properties of bLA, (keeping ratio=small, moving:location)

Again results are bad, so changing again [dCH], this time, changed to bLC, keeping ratio=small (same number of cells), distribution = even(random).

Again results are bad. bPA(green) staying low, bUA(green) staying high, moving to bLC (ratio = smaller), location=middle

Again results are bad, and bPE(blue) is much higher than bPE(green) so going back to dRT(blue) pattern=fill

sticking to dKP, because bPE(blue) high

dKP, so bUP(green) increasing

bPT(blue) is going down, so bST decreasing - new desire to find bPE(green) so going for dCH, using Area with ratio=small distribution=weighted in one corner. reason for ratio=small is because bRS is low (don’t want to take risks).

bPA(green) was low for this test, all the same apart from location and shape.

after that bUA(green) has gone down and so has bUT(green) and thus bPE(green) is low. because bE(blue) is high going back to original scheme dRT

dKP

bPT(blue) still going down and bPA(blue) is now getting low compared to bPB(blue).

thus bST is low and thats causing bRS to get high. Going back to dCH choosing cell-wise again, but this time with ratio=higher and distribution=higher (because of more risk)

it worked! bPA(green) < bPA(blue). continuing with dCH towards green. increasing ratio.

again, improvement on green so dCH towards green. Not going all at once because bRS low, and bUP(green) still not too high.

again, improvement on green. bUP(green) is getting lower. using dCH. going for all green, but with a couple blue because bPT(blue) not certain.

result of using two blue squares has shown that bPA(green) is definitely higher than bPA(blue). bUP is low

dKP bPT(green) increasing, so bST is high

dKP
Although this system turned out to be adequate for creating an agent it had some shortcomings. During the process of extracting the unique beliefs and desires, a lot of scanning back and forth between the list being generated and the narrative text was required. A better system would label unique beliefs and desires within the narratives themselves, so that there is no doubt as to where each desire/belief is expressed within the original narrative transcript. Once all unique desire/belief instances have been labelled, they may then be extracted one-by-one in a second single sweep of the narrative text.

Another problem was with the secondary (intermediate) interpretation. Because the researcher’s own language is used, it creates a layer of abstraction between the original narratives and the final encoded model in which meaning can be changed. A more ideal method would present an intermediate representation which preserves the subject’s original phraseology.

During encoding, the intermediate representation also hindered the encoding of preconditions required to activate desires into intentions. Again, constant referral to the original narratives was required to ensure the exact meaning was being preserved. This problem could have been fixed in a similar manner to the last problem if preconditions expressed were also represented in their original form within the intermediate representation.

### 5.3.3 Encoding the Agent

From the narrative interpretations an artificial agent representing the original human subject was coded. In this initial study the JADEX library for coding BDI agents was used. Within the JADEX BDI model, the core agent implementation is represented as an XML file (Appendix B).
The general structure of the agent definition supplied in the appendix can be summarised as follows:

GOAL [Select Land Use] TRIGGERS:
   PLAN [Select New Pattern] IF:
      curiosity > HIGH
   PLAN [Change and Compare] IF:
      uncertainty > HIGH
   PLAN [Await Trend] IF:
      uncertainty > AVERAGE
   PLAN [Return to Previous] IF:
      previous_good_use != null (a good previous use exists)
      uncertainty_change < AVERAGE
      satisfaction < AVERAGE
   PLAN [Maintain Use] IF:
      previous_good_use == null (a good previous use does not exist)
      satisfaction > VERY_HIGH
   PLAN [Maintain Best] IF:
      true (fallback plan, executed when no other plans viable)

While the core BDI logic is represented within the XML file, any code related to satisfying plans and grounding abstract beliefs in terms of program objects is in the form of separate java class files. These files are called by the JADEX BDI platform during belief revision and plan execution. In this pilot study the majority of the coding effort took place within these class files. The reason for this was that a significant gulf of abstraction existed between the reasoning used by the BDI agent, and the physical simulation objects. For example, the agent’s internal beliefs of ‘curiosity’ or ‘satisfaction’ needed to relate to the changing state of the environment. Similarly, desires such as ‘Maintain Best’ required the agent to possess the notion of land use patterns, and an ability to associate performance with past patterns used.

Measuring Curiosity and Satisfaction

In this agent model, curiosity was determined by calculating an overall uncertainty value. The uncertainty value is a weighted sum of uncertainty in instantaneous profit from each land use, and uncertainty in the profit trend. If a land user constantly alternates the land use then the uncertainty in currently expected profit is minimised because new revenue information is received for both possible land uses in every other
round. While this strategy reduces uncertainty in instantaneous profit expectation, it does not easily allow monitoring of the change in profit over time from each of the uses. This would mean that constantly alternating the land use would increase trend uncertainty for both possible land uses.

If a land user adopts the opposite strategy of leaving land permanently assigned to the same use, then uncertainty in the instantaneous profit and trend of the chosen use gradually drops towards zero. At the same time, uncertainty in profit and trend of the alternative land use gradually rises towards one because no information relating to profit or trend of the alternative use is being received. Neither of the strategies above minimise overall uncertainty. Instead, a strategy of monitoring each land use for a chosen period before switching to the alternative will provide the best trade-off between uncertainty in trends and instantaneous profit of both possible uses.

The satisfaction value was measured by comparing best revenue so far with current revenue, and combining that with the uncertainty value. The assumption is that an agent which is receiving the highest profit so far and has no uncertainty about the expected profits will experience the highest possible value of satisfaction. Increasing uncertainty, or the gap between highest and current profit results in a lower value of satisfaction.

These qualitative measures of curiosity and satisfaction are never assigned a numerical value by the decision maker. Instead qualifiers such as ‘quite’, ‘fairly’ or ‘very’ are used to indicate the level of the measure which activated the stated motive. In order to allow the qualitative values to be used in agent reasoning, numerical threshold values were assigned to each of the stated qualifiers. These threshold values were found by executing the decisions of the original subject and observing the numerical value of the qualitative measure at the point that the original subject uses a qualifier within the narratives. For example, in order to find out the threshold value for ‘fairly’ satisfied, the recorded decision making of the original subject is re-played until ‘fairly satisfied’ is expressed in the narratives. At this point a note of the measured satisfaction value is recorded. The lowest satisfaction value associated with ‘fairly satisfied’ is then used as the threshold value for the ‘fairly’ qualifier, minus a small delta value for tolerance to noise.

**Dealing with Geometric Patterns**
Within this experiment, the use of geometric patterns was an example of previously learned knowledge being applied to the task. In order for the agent to use the same knowledge, the same patterns must be added to the artificial agent’s belief base. Within this methodology, only patterns observed during participatory experiments could be added to the artificial agent’s repertoire of geometric patterns to use. With only a small number of experiments it is not possible to guarantee that a human subject will not use new unseen patterns. A greater number of experiments may remedy this to some degree, but it will never be possible to guarantee that the model uses all patterns that the subject has knowledge of. Direct questioning of the subject with respect to their knowledge of patterns would be more efficient in extracting the information, but this also has problems associated with it. Because the information has not been observed within a simulated land use scenario, the context in which these patterns may be used is not known. Generally, extracting an adequate level of knowledge is an issue for this methodology which requires further research to resolve.

5.3.4 Validation and Results

During the pilot study, an informal comparison of the land use patterns produced by the subject and their representative BDI agent was made. It appeared that the artificial agent generally used a similar overall strategy to the experiment subject, testing small patches of the alternate land use to reduce uncertainty about the expected revenue from applying that use. If it was found that the alternate land use provided better revenue, then the agent would gradually switch all cells to the alternate use, in the same way as the subject. The main differences were in the exact locations and moments in time of use changes. In addition, the artificial agent never made use of any geometric patterns because it required a knowledge base of patterns. These patterns were not implemented into the agent in this pilot study.

The graph in Figure 5.3 compares the number of cells assigned to the blue land use by the subject and the simulated agent at each simulation step. If $n_B$ is the number of blue cells, then the number of green cells at any moment is $25 - n_B$. In order to provide a visual measure of deviation, the difference between the two lines is shaded in grey. The average deviation (Root Mean Squared Error) in the quantity of cells assigned to blue use, between the subject and simulated agent was found to be 3.97 ($\approx 16\%$ normalised). A reasonably low error considering this was the first application
of the methodology, however significant enough to suggest that improvements could be made.

The graph supports the conclusion that the simulated agent matched the general trend of land use assignment, but there were consistent deviations from the exact assignment ratios. Looking at the main transition occurring halfway through, it is clear that the simulated agent was lagging the subject by about 1 time-step during the period of transition from blue to green land use. This may have been caused by slightly incorrect threshold values. If the satisfaction threshold was not set high enough, then the small reduction in satisfaction occurring at the beginning the transition period would not be low enough to trigger a desire to change the land use.

As well as comparing the number of cells assigned to each use, it was also possible to program the artificial agent to output narratives explaining its activities and the reasoning behind them. These are given in Table 5.3. Because the reasoning is generated by a BDI process, it has a fairly direct translation into English language.

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Trying completely new pattern because I’m highly curious about the resulting profit.</td>
</tr>
<tr>
<td>2</td>
<td>Changing the land use pattern because I’m very uncertain about which land use gives more profits.</td>
</tr>
<tr>
<td>3</td>
<td>Changing the land use pattern because I’m very uncertain about which land use gives more profits.</td>
</tr>
<tr>
<td>4</td>
<td>Changing the land use pattern because I’m very uncertain about which land use gives more profits.</td>
</tr>
<tr>
<td>5</td>
<td>Changing the land use pattern because I’m very uncertain about which land use gives more profits.</td>
</tr>
</tbody>
</table>
Table 5.3: Simulated narratives

A subjective comparison of the narratives shows that the artificial agent’s reasoning appears to occur at a higher level than the original subjects’ reasoning, with the real
subject making use of much more in-depth arguments. This is perhaps because some of the distinct motives identified within the narratives could really have been broken down into several. For example, on closer analysis of the subject’s narrative in step 4:

“This land use proved best last year. I repeated my choice to see if the trend would continue the following year.”

It appears as if there are probably two motives expressed. The first is the motive to repeat the choice, while the second (higher-level) motive is to see if the trend will continue. This demonstrates a hierarchical reasoning structure—something that the methodology should handle in order to properly represent human reasoning.

In addition not all behaviours available to the agent are taken advantage of during the simulation. This may be due to the fact that thresholds used may need to be adjusted.

These kind of fine-tuning adjustments were not made in this pilot study, because it will cause confirmation bias. If this approach is to be taken, then a separate data set must be used for validation as was used to build the artificial agent.

Although these validation results do not give a convincing measure of the agent’s performance, they demonstrated the feasibility of the methodology, and highlighted many areas for improvement. The areas for improvement are highlighted below:

1. The GUI needs to provide better visual feedback of revenues. Specifically their relative spatial differences and temporal changes need to be represented.
2. Initial scanning of narratives needs to involve assigning identifiers to uniquely identify beliefs and desires. Identifiers inserted into the original narrative text promote easy identification of the original context in which beliefs and desires appeared.
3. Preservation of original phraseology as far as possible in any intermediate representation of the agent model, constructed during narrative interpretation.
4. Intermediate representation of the agent model needs to specifically represent the preconditions as well as the motives.
5. In order to represent a greater level of reasoning, motives need to be sub-divided into smaller units, with a hierarchical system of reasoning used to select among them.
6. At least two separate data sets need to be taken from the subject. One to be used
for agent development, and another to be used for validation.

5.4 Main Study

Taking into consideration things learned from the initial pilot experiment (listed in the previous section), the main study scaled up the experiments to include a greater number of subjects (nine in total) and slightly more complicated land use scenarios.

5.4.1 Experiment Setup

In the main set of experiments, two different games were played by the subjects. Before the start of the main experiment, subjects were allowed to play a demonstration game to familiarise themselves with the interface. In the demo game, the returned profits from each land use were set to random to prevent any learning in this stage affecting the outcome of the experiments to follow. Although it was not explained that the revenues returned were random, subjects were made aware that revenues raised during the practice game would not count towards the final total and were not important. Subjects were permitted to repeat the short demo game (lasting only 5 rounds), as many times as desired before starting the main experiment. This was to ensure they were comfortable with the GUI, minimising the chances of subjects making mistakes.

5.4.1.1 Game 1

The price-trends used in Game 1 (Figure 5.4) were similar to those used in the pilot study. The price of dark blue started high, gradually decreasing, while the price of light blue started low, gradually increasing. At Round 10 there is a predictable change in the most profitable land use. Exactly half way, at Round 20 there is a large and unpredictable switch back to the prices seen at the beginning of the scenario. From there on the trend seen in the first half is repeated, with light blue gradually increasing and dark gradually decreasing. The trend tests the agent’s ability to recognise and take advantage of trends, as well as testing their ability to handle catastrophic shifts in prices.
In this game, unlike the pilot study, the suitability parameter was used. Figure 5.5 shows the suitability pattern used in the game. The dark blue land cells were configured to return a uniform revenue pattern, while the light blue cells were configured with a pattern which caused cells closer to the centre of the area to return a higher revenue than cells at the outer fringes of the grid. During the transition period, the cells at the centre are the first to outperform the dark land use, with the cells furthest from the centre last to outperform dark blue land use. During the transition periods occurring near rounds 10 and 30, a successful player will tend to change the inner cells to light blue earliest, gradually changing more outer cells as they become more profitable.
5.4.1.2 Game 2

The second game used a more complex trend pattern, designed to challenge the subjects (Figure 5.6). For the duration of the game, the revenue returned by dark green never changes, while light green fluctuates significantly. The game starts with both dark and light land uses returning a very similar profit, with light green slightly outperforming dark. The situation remains stable for seven rounds, during which a successful agent would be expected to have land use predominantly assigned to light green, but with a small number of cells assigned to dark to monitor any changes. On Round 8 there is a slight drop in the profitability of light green so that it drops below dark. In the 10th round this drop is amplified, so that light is now significantly lower than dark. During this period a successful agent would be expected to have caught wind of the change and changed the majority of their cells to the dark land use. The situation again stabilizes for a duration of eight rounds, after which green rises very steeply for a duration of four rounds, until it significantly outperforms dark (by a factor of 286%).

![Figure 5.6: Price trends in light green vs dark green land use](image)

Along with a very unstable price-trend, light green land use also has the suitability parameter configured so that the expected revenue varies spatially. The suitability of the more stable dark green land use is uniform making it a more consistent use, both spatially and temporally. With the spatial pattern used, there are two areas in which the profitability of light green is lowest (bottom-left and top-right corners). During periods in which light green outperforms dark, a successful agent would be expected to make use of these poorly performing cells to test the profitability of dark land use. The suitability patterns are displayed graphically in Figure 5.7.
5.4.2 Experiment Report

In order to find suitable subjects to take part in the experiment, an email (Table 5.4) was sent via various student mailing lists within the University of Edinburgh. Both undergraduates and postgraduates were invited in order to reach a wide as possible audience. The only prerequisites for taking part were that the subject was a student within the University, and was competent at speaking and writing English.

Over the nine-day period subjects took part in the experiments individually. Appointments with subjects were staggered appropriately to ensure that information learned during the experiment was not communicated to other subjects during appointment overlaps. In addition, subjects were asked if they already had knowledge of the system before taking part.

Subjects were supervised during the experiment, to provide assistance where necessary and to ensure it took place according to correct protocol.

During the course of the experiments, feedback was generally positive. Students were content with earnings, which averaged £9.07, with the lowest earned being £7.87, while the most earned was £9.86. This provides a good spread of performance with which to compare decision making strategies.

The narratives recorded from the experiments are listed in Appendix C, along with some general subject data including age, degree topic and study progress. These extra data were collected in order to allow assessment of the subject’s previous relevant
Subject: Land Use Experiment: Earn £10 playing a computer game

Fancy yourself as a farmer? Every year farmers need to decide how to make use of their land resources to ensure they raise enough income to survive.

In this decision making experiment you will be asked to assume the role of the farmer. You will apply uses to your small grid of land cells over a number of rounds, to gain real cash profit. The better your choices, the more money the cells will make for you. You can expect to raise at least 5, and it is possible to make up to 10.

Data collected during the experiment will be used to construct artificial agents which play the game in a similar manner to the original subjects.

Experiments will take place in the next two weeks, between Jan 16th and the 25th. Applicants will be selected on a first come, first served basis. If you are interested please visit site below for more information and details about how to take part: http://xweb.geos.ed.ac.uk/s0127633/expt/

Good luck!

Table 5.4: Email invitation for experiment subjects

Experience, and potential advantages in playing the games. A good quantity of information was provided in most of the narratives provided, and the quality of the English was generally of a high standard. Unfortunately some data from Subject 2’s second game was lost due to a corrupt file.

5.4.3 Narrative Interpretation

Of the nine subjects taking part in the experiment, two were subsequently implemented as BDI agents. First Subject 7 and then Subject 4. They were selected because they had raised above average revenues and appeared to have given the clearest narrative data.

Table 5.5 shows the interpreted narratives of Subject 7. The original narrative text without any interpretation symbols is available in Appendix C. Within the text, as per the methodology outlined in Chapter 4, each belief, motive and precondition is highlighted in blue, green and red respectively. In addition a unique identifier has been added in square brackets for beliefs and motives expressed.
Chapter 5. Case Study 1: Human Decision Making in an Abstract Scenario

<table>
<thead>
<tr>
<th>Key:</th>
<th>Motives, Beliefs (Preconditions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step</td>
<td>Narrative</td>
</tr>
<tr>
<td>1</td>
<td>[m1] Develop all squares evenly</td>
</tr>
<tr>
<td>2</td>
<td>(All squares [b1A] responded uniformly to the selection, all [b1B] positive). [m2] Continue this process.</td>
</tr>
<tr>
<td>3</td>
<td>(All squares [b1B] show a decrease). [m2] Re-select [m1] all to [m8] investigate whether this is a blip or not.</td>
</tr>
<tr>
<td>4</td>
<td>(Decrease [b1B] continues). [m4] Select only half the field to [m8] investigate consequence.</td>
</tr>
<tr>
<td>5</td>
<td>(Sudden drop in half of field that is not selected [b5A]. decrease still evident in selected half [b3B].) [m1] Select whole field to try to [m3] reverse the decline.</td>
</tr>
<tr>
<td>6</td>
<td>(Increase seen once again in selected area [b11]. Area that has been constantly selected [b4] still shows a decline [b4B] however is still green [b4A]) so will [m2] continue with the [m1] whole of the field selected.</td>
</tr>
<tr>
<td>7</td>
<td>(Decline [b3B] still evident.) [m7] Further test cells opened up to [m8] monitor the effects of not selected areas. Having the cells all selected seems to show only minimal decreases in revenue when compared with not.</td>
</tr>
<tr>
<td>8</td>
<td>(Dramatic decrease in areas not selected [b5A].) [m2] Continue with the [m1] selection of all areas [m7] (-2 cells) as (production [b3A] still green)</td>
</tr>
<tr>
<td>9</td>
<td>(Cells not selected [b5A] respond and show increase.) [m7] Deselecting more cells to [m9] try and stimulate increase. (Selected cells [b3B] still showing minimal decrease)</td>
</tr>
<tr>
<td>10</td>
<td>(Minimal increase shown in previously selected cells [b5A]. Decrease continues in selected cells [b3B].) Decide to [m10] let decrease continue until roughly half of scale then [m11] deselect and reselect to [m9] stimulate growth.</td>
</tr>
<tr>
<td>11</td>
<td>[m11] Deselect selected areas. Select those not previously selected.</td>
</tr>
<tr>
<td>12</td>
<td>(Growth seen to be stimulated in some areas [b1B], less uniform [b1A] than before.) [m12] Selecting the areas that did not show any improvement [b9]</td>
</tr>
<tr>
<td>13</td>
<td>(Selected areas [b3B] show overall improvement.) [m2] Keep selected area the same. [m13] Deselect any area that showed a drop [b10]</td>
</tr>
<tr>
<td>14</td>
<td>(Selected areas [b3B] showing a decline. Feel that they might be over exhausted [b3D]) so have [m14] deselected most of the grid. (Areas of the grid [b1B] still showing increase.) [m17] Select areas that are not showing such strong increase [b12]</td>
</tr>
<tr>
<td>15</td>
<td>(Decline shown in areas that have been selected [b3B].) Begin to suspect that (the system needs to ‘recover’ [b3D] after period of use [b3C].) [m14] Deselect all areas.</td>
</tr>
<tr>
<td>16</td>
<td>(All areas [b1B] respond to this.) [m2] Same strategy for this round.</td>
</tr>
<tr>
<td>17</td>
<td>(Increase [b1B] still visible.) [m2]</td>
</tr>
<tr>
<td>18</td>
<td>[m2] As previous.</td>
</tr>
<tr>
<td>19-21</td>
<td>[NONE]</td>
</tr>
<tr>
<td>22</td>
<td>(All areas [b1B] still showing increase.) [m15] No point in attempting to change the strategy</td>
</tr>
</tbody>
</table>
| 23          | (All areas [b1B] crash! disaster. drought most likely.) [m1] Select entire grid to ([m3] try and remediate.) [m6] Leave centre [b2B] unselected (it was the most green) to ([m8] observe observe changes)}
(green areas [b3A] restored. Centre cell [b6] shows increase also.) Considering [m14] deselecting all areas to [m8] see if previous patterns of before (1 round decline then steady increase are shown). Or as before [m2] keep [m1] all selected and [m16] accept slow decline, though (still showing production?) Decide the former.

Worse than feared. (Centre cell [b6] shows increase however all [b1B] have plummeted.) [m5] select worse affected areas [b5B] around outside to [m3] try and remediate

(Increase seen [b11]. Centre areas which were not selected [b6] still increasing.) Decide to [m2] stick with selection pattern for another round.

(Selected areas [b3B] show decrease. Unselected areas [b2A] show increase.) [m14] Deselect all.

(expected decrease [b7] observed.) [m2] leave [m14] all unselected. [m9] hope for increase!

(Increment [b8] observed.) [m2] Continue the strategy

20-35 [NONE]

36 (increase [b8] still observed.) [m2] Continuing, wary of crash as per last time

37 [m15] No point in attempting to change the strategy.

38-40 [NONE]

Table 5.5: Interpreted narratives from Subject 7 - Game 1

Narratives from Game 2 were not interpreted, but instead were kept for the purposes of validation. They are listed in Table 5.9 in the validation section.

After having uniquely identified and labelled each belief, they were compiled into the following list, which clarifies the interpreted meaning of each belief. The list is not expressed using the subject’s original phraseology because expression of beliefs is often vague and sometimes even non-existent (implied by the context). Instead, a clear and concise description is used, designed to promote a straight forward means to encoding them into belief objects. The list is also structured hierarchically, with higher level beliefs (such as ‘selected area’) containing lower-level sub-categories (such as ‘revenue’, ‘change’ and ‘period on use’).

- b1. Revenue from all cells (A:uniformity, B: no.cells growing/decreasing/plummeting (all, some, none))
- b2. Revenue of deselected area (A: overall change, B: most green cells)
- b3. Selected area (A overall instantaneous revenue, B: overall revenue change, C: period on same use, D: Exhaustion level (resulting from period of use))
- b4. Overall revenue of area selected previously (A: instantaneous value, B: change)
- b5. Change in revenue from cells which were selected and now deselected (A: overall, B by cell)
- b6. Change in revenue of unselected cells which were also unselected previously
- b7. Expected change in revenue from switching to the alternative land use allocation.
- b8. Expected change in revenue from maintaining the same land use allocation.
- b9. Test cells which did not show any improvement
- b10. Selected areas which showed a drop.
- b11. Change in revenue from cells which were deselected and now selected
- b12. Deselected areas which are not showing a strong increase

Based on the lessons learned from the pilot study, an agent schema was constructed (Table 5.6), in which only the subject’s original phraseology was preserved. Where motives and beliefs are expressed within the schema, the unique identifiers are used to ensure there is no ambiguity within the model. For each precondition, a note of recently activated motives is given as the ‘context’. The reason this was done is because the recent context of a subject’s reasoning is also a driver of future behaviour. Because context is maintained naturally when we read, the subject does not expect the reader to need the context to be re-expressed for every new narrative. However, because the model removes the original ordering of the narratives, the original context information is lost. Adding a context to each precondition allows the model to take the original context into consideration along with the environmental conditions.

In this interpretation, care was taken to break down narratives with multiple constituent motives. Many instances of higher-level motives raising sub-motives were found. As a result, a lot more of the deliberation involves internally raising sub-motives. In the previous model constructed in the pilot study each motive or ‘desire’ had an action directly associated with it, so that commitment to a desire directly translated into execution of a plan of action. In this model however, there are higher level motives such as ‘[m9] stimulate growth’ which, instead of directly executing plans, raise lower level motives such as ‘[m7] open up test cells’, ‘[m11] deselect and reselect’ or ‘[m2] continue the strategy’, depending on preconditions. This keeps all reasoning within the core BDI system, so that it maintains deliberative reasoning, while at the same time allowing reactive behaviour.

Where a motive raises sub-motives within the model, the precondition in which the new motive was raised uses the raise=[m_] terminology to express which motive should be activated. Similarly, if commitment to a motive causes another one to be dropped, the precondition in which this occurs uses the terminology drop=[m_]. For motives which are raised by higher level ones, the precondition ‘raised by [m_]’ is used to indicate that the motive may be triggered by internal deliberation, rather than changes in external conditions.
Finally, where motives have parameters associated with them which vary depending on environmental conditions, a note is made of the parameter value when each precondition was expressed. For example, for the motive ‘[m7] further test cells opened up’, there is a parameter c (number of cells) associated with it. If the value for that parameter is expressed within the narratives, then the causative precondition will be expressed along with the value of the parameter chosen. Within the model this is expressed after the precondition as an assignment statement. For example, the second precondition for m7, has the value c=2 associated with it.

<table>
<thead>
<tr>
<th>Motive</th>
<th>Precondition(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>m1. Develop all squares evenly</td>
<td>(start of simulation)</td>
</tr>
<tr>
<td>m1. Select whole field</td>
<td>OR</td>
</tr>
<tr>
<td>m1. Whole of the field selected.</td>
<td>(raised by [m3])</td>
</tr>
<tr>
<td>m1. Selection of all areas</td>
<td></td>
</tr>
<tr>
<td>m1. Select entire grid</td>
<td></td>
</tr>
<tr>
<td>m1. All selected</td>
<td></td>
</tr>
</tbody>
</table>
m2. Continue this [x] process.
m2. Re-select x
m2. Continue with x
m2. Same strategy [x] for this round.
m2. As previous. [x]
m2. Keep x
m2. Stick with selection pattern [x] for another round.
m2. Leave x
m2. Continue the strategy [x]
m2. Continuing x

(All squares [b1A] responded uniformly to the selection AND all [b1B] positive AND context [m1] | x=[m1])
OR
(raised by [m8] AND context [m1] | x=[m1])
OR
(Increase seen once again in selected area [b11]. AND Area that has been constantly selected [b4] still shows a decline [b4B] AND is still green [b4A] AND context [m3,m1] | x=[m1])
OR
(Dramatic decrease in areas not selected [b5A]. AND production [b3A] still green AND context [m7,m1] | x=[m1])
OR
(All areas [b1B] respond to this. AND context [m14] | x=[m14])
OR
(Increase [b1B] still visible. AND context [m14] | x=[m14])
OR
(Increase seen [b1B]. Centre areas [b2A] which were not selected still increasing. AND context [m5] | x=[m5])
OR
(raised by [m9] AND context [m14] | x=[m14])
OR
(Increase [b8] observed. AND context [m14] | x=[m14])
OR
(increase [b8] still observed. AND context [m14] | x=[m15])
OR
(Selected areas [b3B] show overall improvement. AND context=[m12] | raise=[m13])

m3. Try and remediate.
m3. Reverse the decline

(All areas [b1B] crash! disaster. drought most likely. AND context [m14] | raise=[m1,m8])
OR
(Centre cell [b6] shows increase AND all [b1B] have plummeted. AND context [m8,m14] | raise=[m5])
OR
(Sudden drop in half of field that is not selected [b5A]. AND decrease still evident in selected half [b3B]. AND context [m8,m4] | drop=[m4], raise=[m1])

m4. Select only half the field
raised by [m8] | drop=[m1]

m5. Select worse affected areas [b5B] around outside
raised by [m3]
<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>m6.</td>
<td>Leave centre [b2B] unselected (it was the most green) raised by [m8]</td>
</tr>
<tr>
<td>m7.</td>
<td>Further test cells opened up (raised by [m8])</td>
</tr>
<tr>
<td>m7.</td>
<td>(-c cells) (raised by [m2]</td>
</tr>
<tr>
<td>m7.</td>
<td>Deselecting more cells (raised by [m9])</td>
</tr>
<tr>
<td>m8.</td>
<td>Monitor the effects of not selected areas (All Squares [b1B] show a decrease AND context [m1]</td>
</tr>
<tr>
<td>m8.</td>
<td>Observe changes (Decrease [b1B] continues AND context [m1,m8]</td>
</tr>
<tr>
<td>m8.</td>
<td>See if previous patterns of before (1 round decline then steady increase are shown) (Decline still evident [b3B] AND context [m1]</td>
</tr>
<tr>
<td>m8.</td>
<td>Investigate whether this is a blip or not. (raised by [m3]</td>
</tr>
<tr>
<td>m8.</td>
<td>Investigate consequence (raised by [m9]) (green areas [b3A] restored. AND centre cell [b6] shows increase also. AND context [m1,m8]</td>
</tr>
<tr>
<td>m9.</td>
<td>Try and stimulate increase. (Cells not selected [b5A] respond and show increase. AND Selected cells [b3B] still showing minimal decrease AND context [m1,m7]</td>
</tr>
<tr>
<td>m9.</td>
<td>Stimulate growth (raised by [m10]</td>
</tr>
<tr>
<td>m9.</td>
<td>Hope for increase! (expected decrease [b7] observed. AND context [m14]</td>
</tr>
<tr>
<td>m10.</td>
<td>Let decrease continue until roughly half of scale (Minimal increase shown in previously selected cells [b5A]. Decrease continues in selected cells [b3B]. context [m1,m7]</td>
</tr>
<tr>
<td>m11.</td>
<td>Deselect and reselect raised by [m9]</td>
</tr>
<tr>
<td>m11.</td>
<td>Deselect selected areas. Select those not previously selected.</td>
</tr>
<tr>
<td>m12.</td>
<td>Selecting the areas that [b9] did not show any improvement Growth seen to be stimulated in some areas [b1B] AND less uniform [b1A] than before. AND context [m9,m11]</td>
</tr>
<tr>
<td>m13.</td>
<td>Keep selected area the same. Deselect any area that [b10] showed a drop (Selected areas [b3B] show overall improvement. AND context [m12])</td>
</tr>
</tbody>
</table>
m14. Deselect all areas.
m14. Deselecting all areas
m14. Deselect all.
m14. All unselected
m14. Deselected most of the grid.

(Decline shown in areas that have been selected [b3B].) Begin to suspect that (the system needs to ‘recover’ [b3D] after period of use [b3C]. AND context [m12] | drop=all)
OR
(raised by [m2])
OR
(Selected areas [b3B] show decrease. AND Unselected areas [b2A] show increase. AND context [m5] | drop=[m5])
OR
(Selected areas [b3B] showing a decline. Feel that they might be over exhausted [b3D] | raise=[m17])

m15. No point in attempting to change the strategy

All areas [b1B] still showing increase. | inhibit= [m1,m4,m7,m8,m9,m12,m13,m14,m3,m5]

m16. Accept slow decline
never activated

m17. Select areas that [b12] are not showing such strong increase
raised by [m14]

Table 5.6: Agent schema for Subject 7

All instances of the original phraseology are preserved within the agent schema, so that meaning is preserved as far as possible. This also facilitates the process of generating artificial decision narratives which use the same language as is used by the original subject.

Table 5.7 shows the interpreted narratives of Subject 4, recorded during Game 1. As before, the original narrative text without any interpretation symbols is available in Appendix C.

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[m1] Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>[m2] Leaving them the same as (all [b1A] seem to have started off making ok money)</td>
</tr>
<tr>
<td>3</td>
<td>(Top left square losing some money [b2B] - but still making ok money [b2A]) so will [m2] leave it.</td>
</tr>
<tr>
<td>4</td>
<td>Going to [m3] change the landuse of A5, E1, E5 as ([b3A] making the least money)</td>
</tr>
<tr>
<td>5</td>
<td>Going to [m2] leave land use the same this round because ([m4] want to see what happens) and (even though the top left box [b2A] is losing money - its only a little bit)</td>
</tr>
<tr>
<td>6</td>
<td>Going to [m3] change some of the landuse for the top left square (A1, A2, A3) just to ([m4] see what happens and if this increases revenue)</td>
</tr>
<tr>
<td>7</td>
<td>Going to [m5] change landuse of A1 back to dark as ([its the square [b3A] earning the least amount of money and its going down [b3B])]</td>
</tr>
</tbody>
</table>
[m2] Leaving squares as they are as (they [b1A] seem to be ok at the moment)

Going to [m3] change landuse on squares D1 and D5 to landuse dark as (they [b3A] are a couple of the squares earning the least amount of money)

[m3] Changing squares A2, A4, B5, E2, E4 as ([b3A] earning least amount of money)

last round was left the same - this round is that reason (sorry conrad)

[m3] change squares c3, b3, c2 to landuse light to ([m6] see if it is affected by landuse of higher revenue close by)

going to [m3] change land use of b2 and c1 as ([b4] close to other areas doing well)

[m2] leaving the same for this round to ([m4] observe what happens)

[m3] changed the landuse of the areas b1, d1, b5, d5 as (these areas [b2A] are losing money and are [b4] close to areas doing better)

(that last idea [b5] didn’t work) ... going to [m2] leave it the same this round

[m3] changing landuse of all (the areas [b2A] doing the worst in terms of money and are also losing money) - so changing a1 a2 a3 a4 e1 e2 e4 e5 - all areas are light landuse

[m2] leaving the same landuse as the last round

[m2] leaving same landuse as last round

(all areas [b1A] are making money) so [m2] leaving landuse the same

[NONE]

[NONE]

(all landuse [b1A,b1B] went really bad) so [m3] changing the border to dark landuse as (the whole area went to losing money and they are the worst performing areas [b6])

(all areas [b1A] back to making money) so are [m2] going to leave landuse the same

going to try and [m3] change landuse of b2, b4, d2, d4 to dark to ([m4] see if can increase profit on these areas)

[m3] changing land use of e4, e5 to light to ([m4] see if can increase profit these are a couple of the areas [b1B] losing money)

[m5] changing e4 and e5 back to dark as (they [b3A] are not making much money at all)

[m2] leaving the same landuse as last round

[m3] changing landuse of a1, a2, b1, b2 to ([m4] see if light landuse will increase profits)

(this [b5] didn’t work) so will [m5] change those four areas back to dark land use

[m2] leaving areas as the same

(losing money on all the dark areas [b2A]) so [m3] changing b2, b4, d2, d4 to light as (areas close by [b4] are doing better)

[m3] changing area c1 and c5 to light as (areas close by [b4] are doing ok)

(that [b5] didn’t really work) - so are going to [m5] change them back to dark land use

[m2] leaving land use the same

(losing money on the border area [b2A] of dark) - so [m3] going to try changing a1-a3 to landuse light

(only a3 [b3B] improved on the last round) so going to [m3] change c1, c5, and e3 to light and [m5] a2 and a4 back to dark

going to [m3] change b1, b5, d1, d5 to land use light so ([m6] see if close association to areas doing better helps)
 Compared to Subject 7, Subject 4 appeared to express a larger number of motives without any preconditions; for example, motives expressed in rounds 5, 6, 12, 14, 18, 19, 25, 28, 29, 31, 35, 38, 39 and 40. Whether this is a result of mistaken omission, or proactive behaviour is difficult to tell. Although follow-up questions could be used for confirmation, doing so may bias the model towards displaying more reactive behaviour because of post-justification. In asking for the reason something was done, an interviewer is implying that an observable reason must exist.

When proactive behaviour is expressed, the only causative factor which can be taken from the narratives is context. Within the context, these behaviours must be assumed to be random events with a certain probability of occurrence. Using the narratives, the probability of occurrence of these behaviours can be estimated by analysing how often they are expressed without any precondition.

The unique beliefs used by Subject 4 within this narrative were compiled into the following list:

- b1. All cells (A: average profit level, B: change in profit)
- b2. An area of cells (A: average profit level)
- b3. Specific cell (A: profit level, B: change in profit)
- b4. Cells close to other cells doing well
- b5. Previous approach/strategy
- b6. Cells with lowest revenue

Again, narratives from Game 2 were not interpreted, but instead are kept for the purposes of validation. They are listed in Table 5.11 in the validation section.

The agent schema constructed from Subject 4’s interpreted narratives is presented in Table 5.8.

<table>
<thead>
<tr>
<th>Motive</th>
<th>Precondition(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>[m2] leaving the same landuse</td>
<td></td>
</tr>
<tr>
<td>[m3] changing a2 a4 land use to light to ([m4] see if it improves profit)</td>
<td></td>
</tr>
</tbody>
</table>
### Case Study 1: Human Decision Making in an Abstract Scenario

<table>
<thead>
<tr>
<th>m1. Top left dark square (3x3) to start with all the same land-uses grouped together</th>
<th>(start of simulation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>m2. Leaving them the same</td>
<td>(none)</td>
</tr>
<tr>
<td>m2. leave land use the same this round</td>
<td>OR (raised by [m4])</td>
</tr>
<tr>
<td>m2. Leaving squares as they are</td>
<td>OR (all [b1A] seem to have started off making ok money AND context [m1])</td>
</tr>
<tr>
<td>m2. leaving the same for this round</td>
<td>OR (Top left square losing some money [b2B] - but still making ok money [b2A] AND context [m2])</td>
</tr>
<tr>
<td>m2. leave it the same this round</td>
<td>OR (they [b1A] seem to be ok at the moment)</td>
</tr>
<tr>
<td>m2. leaving the same landuse as the last round</td>
<td>OR (that last idea [b5] didn’t work AND context [m3])</td>
</tr>
<tr>
<td>m2. leaving squares as they are</td>
<td>OR (all areas [b1A] are making money)</td>
</tr>
<tr>
<td>m2. leaving the same landuse</td>
<td>OR (all areas [b1A] back to making money AND context [m3])</td>
</tr>
<tr>
<td>m2. leaving the same landuse as last round</td>
<td></td>
</tr>
<tr>
<td>m2. going to leave landuse the same</td>
<td></td>
</tr>
<tr>
<td>m2. leaving the same landuse as last round</td>
<td></td>
</tr>
<tr>
<td>m2. leaving areas as the same</td>
<td></td>
</tr>
<tr>
<td>m2. leaving land use the same</td>
<td></td>
</tr>
<tr>
<td>m2. leaving the same landuse</td>
<td></td>
</tr>
</tbody>
</table>
m3. change the landuse of A5, E1, E5
m3. change some of the landuse for the top left square (A1, A2, A3)
m3. change landuse on squares D1 and D5 to landuse dark
m3. Changing squares A2, A4, B5, E2, E4
m3. change squares c3, b3, c2 to landuse light
m3. change land use of b2 and c1
m3. changed the landuse of the areas b1, d1, b5, d5
m3. changing landuse
m3. changing the border to dark landuse
m3. change landuse of b2, b4, d2, d4 to dark
m3. changing land use of e4, e5 to light
m3. changing landuse of a1, a2, b1, b2
m3. changing b2, b4, d2, d4 to light
m3. changing area c1 and c5 to light
m3. going to try changing a1-a3 to landuse light
m3. change c1, c5, and e3 to light
m3. change b1, b5, d1, d5 to land use light
m3. changing a2 a4 land use to light

(raised by [m4])
OR
(raised by [m6])
OR
([b3A] making the least money AND context [m2])
OR
(they [b3A] are a couple of the squares earning the least amount of money AND context [m2])
OR
([b3A] earning least amount of money)
OR
([b4] close to other areas doing well AND context [m6])
OR
(these areas [b2A] are losing money and are [b4] close to areas doing better AND context [m2,m4])
OR
(the areas [b2A] doing the worst in terms of money and are also losing money AND context [m2])
OR
(all landuse [b1A,b1B] went really bad AND context [m2])
OR
(losing money on all the dark areas [b2A] AND areas close by [b4] are doing better AND context [m2])
OR
(areas close by [b4] are doing ok AND context [m3])
OR
(losing money on the border area [b2A] of dark AND context [m2])
OR
(only a3 [b3B] improved on the last round AND context [m3])

m4. want to see what happens
m4. see what happens and if this increases revenue
m4. observe what happens
m4. see if can increase profit on these areas
m4. see if can increase profit these are a couple of the areas losing money
m4. see if light landuse will increase profits
m4. see if it improves profit

(even though the top left box [b2A] is losing money - its only a little bit AND context [m3] | raise [m2])
OR
(context [m2, m4] | raise [m3])
OR
(context [m2] | raise [m3])
OR
(context [m3] | raise [m2])
OR
(context [m3] | raise [m3])
m5. change landuse of A1 back to dark
   m5. changing e4 and e5 back to dark
   m5. change those four areas back to dark land use
   m5. change them back to dark land use
   m5. a2 and a4 back to dark
   (its the square [b3A] earning the least amount of money and its going down [b3B] AND context [m3, m4])
   OR
   (they [b3A] are not making much money at all AND context [m4,m3])
   OR
   (this [b5] didn’t work AND context [m4,m3])
   OR
   (that [b5] didn’t really work AND context [m3])
   OR
   (only a3 [b3B] improved on the last round AND context [m3])

m6. see if it is affected by landuse of higher revenue close by
   m6. see if close association to areas doing better helps
   (context [m3] | raise [m3])

Table 5.8: Agent schema for Subject 4

5.4.4 Encoding the Agent

An attempt was made to encode the more complex agent model representing Subject 7 within the framework provided by the JADEX BDI library. Although the library provides the necessary facilities for the task, the way in which JADEX is structured prevents any ‘goals’ (desires) from directly raising new goals. Instead a plan needs to be created for the goal. This involves specifying a plan within the XML schema. Each plan within the XML schema, then requires a new Java class file in which the body of the plan is specified. Only within the java implementation of the plan body can any sub-goals be raised. This structure is not only very verbose, but also departs from the BDI philosophy somewhat, in that it requires every goal (desire) to have plan(s) of action associated with it. Since not all desires lead directly to action, it makes sense to structure the system so that executed motives may directly raise new ones.

To this end, a basic BDI platform was constructed, centred around the concept of individual ‘Motive’ objects. Each motive object contained two key methods. A service() method (called when the motive is active and has become an intention), and an isViable() method, called during the motive selection process. Within the framework, plans are specified within the service() method, where they may call other methods to
generate actions, or raise new motives as required. The key difference between this framework and JADEX is that planning remains an intrinsic part of the BDI reasoning process, rather than being left external to the core BDI reasoning process.

The models representing agents 7 and 4 are fairly complex, and for the purposes of brevity they are placed within appendices D and E. Compared to the model produced in the pilot study, these are more in-depth, breaking motives down into finer detail and using a more elaborate set of preconditions to execute these motives.

Again, similarly to the last study, a significant effort was made in grounding the agents. It allowed both: (1) high level actions (outputs) to be specified in terms of low level actions available within the model, and (2) high level beliefs to be specified in terms of low-level data available within the model environment.

5.4.5 Validation and Results

In order to test how well the agent models replicate the behaviour of their respective subjects, their output was compared with the output produced by the original subject. Four aspects were compared:

1. **Performance Trend**: A round-by-round comparison of the subject and agent’s competence by analysing proximity to the optimal choice.
2. **Land Use Trend**: A comparison of the total number of cells allocated to each land use by the subject and agent in each round.
3. **Spatial Land Use Pattern**: Comparing the ability of players to take advantage of the spatial heterogeneity in returned revenues by using a statistical measure of spatial correlation.
4. **Narratives**: A direct comparison of the narratives generated by the subject and agent at common time points to establish whether the underlying semantics of the narratives are the same.

5.4.5.1 Subject 7: Approach

**Measuring Simulation Error**: The agent model for subject 7 contains only reactive behaviours. As a result decision making is largely deterministic. The only random ele-
ment in the decision making is that of the location of ‘sample’ cells. Because validation is with respect to the second game, there is only one set of data trends to compare with the subject. In order to compare the similarity of the subject and its agent, temporal plots were created for each quantitative validation dataset, with the deviation between them highlighted by shading in grey.

A statistical measure of the deviation between the temporal plots was calculated using the root mean squared error (RMSE). It is calculated using

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (M_i - O_i)^2}$$

(5.1)

where $O_i$ is the value observed from the subject in the $i^{th}$ round, $M_i$ is the value generated by the model, and $n$ is the number of rounds.

**Measuring Spatial Correlation:** In order to measure the correlation between a player’s land use allocation and the spatial revenue pattern, it was necessary to measure the relative advantage of selecting one use over the alternative in each cell. This was done by calculating a utility value associated with selecting each possible land use. By taking a cell specific measure of the utility value of each use and the allocation made by a player it is possible to gain a measure of spatial correlation. That is correlation between land use allocation and the utility of that allocation.

The utility value is calculated using

$$U_{i,j,dark} = \frac{R_{i,j,dark} - R_{i,j,light}}{R_{i,max} - R_{i,min}}$$

(5.2)

where $R_{i,j,dark}$ is the revenue generated by selecting dark use on the $j^{th}$ cell in the $i^{th}$ round; $R_{i,j,light}$ is the revenue generated by allocating light use; $R_{i,max}$ is the maximum generated by any cell in the $i^{th}$ round; and $R_{i,min}$ is the minimum revenue. The utility value is in the range $-1 \leq U \leq 1$, and describes the utility of selecting dark over light land use for the given cell in the given round.

In order to find the spatial correlation with land use, the Point Biserial Correlation Coefficient (Hopkins, 1995) is calculated, using the continuous utility value from equation 5.2, under each of the possible land uses as follows
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\[ r_i = \frac{(\bar{U}_{i,dark} - \bar{U}_{i,light}) \sqrt{P_{i,dark}P_{i,light}}}{\sigma_{U,i}} \]  

(5.3)

where \( \bar{U}_{i,dark} \) is the mean utility of dark use in the \( i^{th} \) round; \( \bar{U}_{i,light} \) is the mean utility of light; \( P_{i,dark} \) is the proportion of cells assigned to dark in the \( i^{th} \) round; \( P_{i,light} \) is the proportion of cells assigned to light; and \( \sigma_{U,i} \) is the standard deviation in all utility values in the \( i^{th} \) round. The calculated correlation coefficient is in the range \(-1 \leq r \leq 1\). A positive value indicates that the decision maker was able to take advantage of the underlying spatial variation in revenues. A negative value indicates that the land use allocation was counter to that which would take advantage of the spatial variation, and a value of zero indicates that the decision for that round neither took advantage of, nor was negatively impacted by the underlying spatial variation in revenues.

5.4.5.2 Subject 7: Performance Trend

In order to measure the performance of agents the proximity of their land use allocation to the optimal allocation was calculated. The optimality value ranges between 0 and 1. A value of 1 is the result of choosing a land use allocation generating the maximal possible revenue for the round. The optimality level is calculated by dividing the revenue earned by the maximum possible revenue available in that round. The graph in Figure 5.8 shows the optimality of the human subject and simulated agent in each simulation round. The black line is for the human subject, while the grey one is for the agent. The deviation between the two is shaded in grey.

![Real vs Simulated Optimality - RMSE: 0.06](image)

Figure 5.8: Subject vs agent optimality in each round
The very low level of deviation between the two lines ($RMSE = 0.06$) indicates that both agents are capable of bringing about a very similar state of affairs in terms of game performance. This indicates that the agents share a similar level of success. While this may at first be encouraging, it does not necessarily mean that they are making the same choices. Whether this result indicates a similar reasoning is taking place is difficult to tell. In order to provide a better view into the reasoning taking place, it is necessary to analyse the actual land use allocations of the players. This will give more insight into whether the players use the same strategy to achieve the same general performance.

### 5.4.5.3 Subject 7: Land Use Trend

Figure 5.9 shows the number of cells assigned to the dark land use at each step in the simulation. The subject’s allocation is in black, while the simulated agent’s allocation is in light grey. The area of deviation between the two trends is shaded in grey as before.

![Figure 5.9: Number of cells assigned to dark land use](image)

It is clear that in the beginning of the simulation, when there is little difference between the relative payoff of both land uses, the level of deviation is very high. Just after Round 10, when dark has a clear advantage over light, both the subject and agent have similar land use choices. Both assign a certain number of ‘test cells’ to the alternative use to maintain a view of the changes in its profitability. The difference is that the subject changes the number of test cells applied, and appears to show earlier signs of reacting to the increase in profitability of light green. The subject begins to make changes in Round 18, compared to the agent which starts making changes in Round
20. However, both change the majority of their cells at the same time (Round 21), and there is significant agreement between the two in the final stages of the simulation. In general it appears as if the deviation is greatest when the relative profit between the two alternative land uses is at its lowest. The larger levels of deviation between these two trends is reflected by the higher root-mean-squared error ($RMSE = 10.0$).

### 5.4.5.4 Subject 7: Spatial Land Use Pattern

The land use graph allows good temporal comparison between the subject and agent, but how do we know how closely their spatial land use choices match? In order to provide a visual indication, the land use assigned to each cell is added up over the period of the game to give the total number of times that cell was assigned to a particular use. In this case the number of times the cell was used on the dark land use was added. Because each cell may only be used for either light or dark, the number of times the cell was used on light use can be calculated by taking the number of rounds (30) and subtracting the number of times the cell was used on dark. Figure 5.10 shows the temporally cumulative, spatial pattern of land use for both the subject and agent.

![Figure 5.10: Number of rounds on dark land use: real vs simulated](image)

Again, the large error of deviation ($RMSE = 6.70$), and darker overall look of the simulated land use pattern is explained by the significant deviation at the beginning of the simulation. Taking the deviation into account, the spatial pattern produced by the subject (Figure 5.10 on left) shows a bias towards the top left and bottom right corners. This would indicate that the subject made choices which took advantage of the underlying spatial differences in the suitability map (Figure 5.7). In the pattern
produced by the simulated agent, there appears to be a negative bias in the bottom left area (as would be expected), but the top right does not show the same negative bias. This may be because in earlier rounds of the game the agent chose a predominantly dark land use pattern in which spatial revenue payoff is uniform. It appears that most random ‘sampling’ of the alternative use occurred in the bottom-left corner, rather than being evenly distributed among all areas.

The plot shown in figure 5.11 shows the Point Biserial Correlation Coefficient between land use allocation and utility of individual cells in each round (as described in 5.4.5.1). It shows that both the subject and agent generally fail to take advantage of the spatial heterogeneity in cell revenues. During earlier rounds the subject generally adopted circular or square patterns centred on the middle of the area. This would have been an advantageous strategy in the first game, but resulted in zero correlation with the spatial pattern in this game. However in rounds 8, 18, 19 and 20 the subject adopts a diagonal land use pattern with close correlation to the underlying spatial revenue pattern. This is illustrated by the high correlation statistic during these rounds. It appears that the subject was able to recognise the relative advantage of cells towards the top-right and bottom left for dark land use. There is also a hint of this behaviour in the agent during rounds 16 and 17, but the level of correlation is much weaker because the agent only assigns a small proportion of light cells in the correct areas.

![Figure 5.11: Number of cells assigned to dark land use](image)

5.4.5.5 **Subject 7: Narratives**

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
</table>
Select whole area minus center cell to observe the effect
Decline across the board! Will continue with selection to try and gauge effect. Selecting only half the cells.
Deselected cells show increase. Remainder of cells show no change( cannot get any worse perhaps?) Deselect all
increase seen in newly deselected cells. No change in others. Continue with lack of selection to observe
Single cell previously selected showed decline. No change observed in other cells. Select on cell to observe.
No change. Selected cell shows improvement. No change in rest. Continue to observe
No change. Select top line to see if some improvement can be stimulated
Increase seen in some cells, decrease in others. Decide to select all cells.
More varied performance. Area seems to be responding in quarters, 2 showing growth. Select two that have increased positively
Areas not selected show increase. Areas selected bomb. Deselect all.
Increase seen uniformly. Leave all not selected, select random squares to monitor
Selected areas show increase. Others sharp decrease. Select all except areas that have responded previous round
All areas respond and increase except those not selected. Continue with strategy
No improvement seen. All areas still poor. Annoying
Random areas deselected to see results.
Areas show decrease. Will continue to observe
All areas stagnant. :( No improvement seen. Selecting all to max figures. Cannot seen to stimulate growth!
Select areas that are showing values of less than 50.
Decrease in those areas. Continue
No effect observed. Continue
Ah ha! at last. Areas left unselected show increase. Deselect all areas
All areas respond. Continue
Profits off the scale. Fear crash. :P
Revenue plateau’d out. Selecting one cell to observe change.
Decrease in cell. Reselect and continue.
No change observed.
No reason to change
[NONE]
[NONE]

Table 5.9: Recorded narratives from Subject 7 - Game 2

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Develop all squares evenly.</td>
</tr>
<tr>
<td>2</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>
Further test cells opened up to monitor the effects of not selected areas.

Cells not selected respond and show increase. Deselecting more cells to try and stimulate increase. Selected cells still showing minimal decrease.

Further test cells opened up to monitor the effects of not selected areas.

[NONE]

Further test cells opened up to monitor the effects of not selected areas.

[NONE]

Further test cells opened up to monitor the effects of not selected areas.

Dramatic decrease in areas not selected. Continue with the selection of all areas (-2 cells) as production still green.

Further test cells opened up to monitor the effects of not selected areas.

Deselect all areas to stimulate growth.

Increase still visible. As previous. expected decrease observed. leave all unselected. hope for increase!

expected decrease observed. leave all unselected. hope for increase!

Table 5.10: Simulated narratives for Subject 7, Game 2

The real narratives recorded from Subject 7 are presented in Table 5.9, and the simulated narratives from the artificial agent appear in Table 5.10. Remember that absolutely no data from Game 2 was used in constructing the artificial agent, which means that the phraseology used in generating the narratives (along with the reasoning behind them), comes only from data recorded in the first game.

Looking at the first stage of the experiment, it is clear that significant deviation exists in the reasoning, which explains the significant deviation in land use choices. The simulated agent tends to stick to the same strategy of keeping a small number of cells to test the alternative land use, while predominantly maintaining the dark (‘selected’) land use. Although the reasoning is different at the early stages, in the mid stages, both appear to be using a similar strategy. Quoting the subject half way through the second period of the simulation (Round 15):

“Random areas deselected to see results.”

While during most of this stage the simulated agent produces the narrative:

“Continue with the selection of all areas (-2 cells) as production still green.”

Although the narratives are different, the meaning within is similar. Continuing with the same selection ‘minus two cells’ is a reference to the strategy of sampling random
cells to monitor the revenue of the alternative use.

Again there is similarity between the subject and agent at the key transition period around Round 21 when light green land use suddenly becomes much more profitable than dark. The narrative produced by the real subject is:

“Ah ha! at last. Areas left unselected show increase. deselect all areas”

While the simulated agent produces:

“Deselect all areas to stimulate growth.”

Although the exact terminology used varies, the general strategy and reasoning for it appears to have some agreement during the latter part of the simulation, which explains the correlation between real and simulated land uses in the final two-thirds of the simulation.

### 5.4.5.6 Subject 4: Approach

A major difference between the behaviour of Subject 7 and Subject 4 is that the latter seemed to express much more proactive behaviour. These are behaviours in which the impetus behind them is not expressed in terms of the state of the environment. When implemented as an agent model, these behaviours are initiated as random events with a certain probability of occurrence. The resulting behaviour can deviate quite significantly, depending on exactly when these random events are triggered. As a result, it was necessary to carry out multiple simulation runs, using the standard deviation and the chi-square test to compare observed and simulated behaviour.

A Monte Carlo hypothesis test, described in Waller et al. (2003) is used for validating data from Subject 4. The general principal is to reverse the traditional approach of establishing “whether the model falls within the observed variability of the data”, to testing “whether the data falls within the observed variability of the model”. This methodology for validation is well suited to situations in which observed data is limited, but where simulated data is abundant. In such situations it is difficult or impossible to measure the variability of the system under observation, but easy to measure the inerrant variability in the model. Whether the model is able to reproduce the variability of the observed system cannot be tested. What the test can establish is the probability
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that the observed data is consistent with the behaviour of the model and its variability.

For each of the validation data sets, the null hypothesis is set up as follows:

\[ H_0 : \text{The observed data appears to be a typical realisation of the model.} \] (5.4)

Where the null hypothesis must be rejected the alternative is:

\[ H_a : \text{The observed data does not appear to be a typical realisation of the model.} \] (5.5)

In order to establish whether the observed data fits the model, the chi-square statistic is used. It was calculated as

\[ X^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{\sigma_i^2} \] (5.6)

where \( O_i \) is the observed value for the \( i^{th} \) round, \( E_i \) is the expected (mean) value generated by the agent model, \( \sigma_i \) is the standard deviation in the values generated by model, and \( n \) is the total number of rounds.

The \( P \) value is then calculated from \( X^2 \), assuming \( n - 1 \) degrees of freedom. For this validation a 5% significance level is used (\( \alpha = 0.05 \)). If the \( P \) value is less than alpha (\( P < \alpha \)) then it is decided that the observed data lies too far outside of the modelled mean, (considering the modelled level of deviation) for at least 95% confidence level, and the null hypothesis \( H_0 \) is rejected.

A sample of thirty simulation runs were used to gather the validation data required for subject 4. Detailed data for the first ten of those runs (including land use trends and narratives) are available in Appendix F.

5.4.5.7 Subject 4: Performance

The graph of optimality in Figure 5.12, shows that both the subject and agent were able to achieve close to optimal revenues for most of the simulation rounds. The dip in performance from rounds 20 to 25 illustrates the effect of the slow response to the extreme change in revenue returned by light land cells. The greater deviation in the simulated result around this time point reflects differences in agent response times across different simulation runs.
Generally there is quite good agreement between these two graphs. The chi-square statistic for these data yields $P \approx 1.000$ thus $P \geq \alpha$. Statistically, we accept $H_0$ meaning that for at least a 95\% confidence level the observed data could have been derived from the model.

5.4.5.8 Subject 4: Land Use Trend

The graph in Figure 5.13 shows for each round, the recorded allocation of the subject in black, the mean simulated allocation in grey, and the shaded area either side of the grey line shows the standard deviation.
between the real and simulated allocations. The early rounds (1-10) and later rounds (21-30) show a greater difference between the real and simulated allocation. In both cases, the agent is assigning more cells to the dark land use than the subject did. In the early rounds, both the subject and agent adopt the behaviour of predominantly choosing the light land use, while sampling the alternative use to monitor for changes. Unlike Agent 7, sampling seems to take place within a contiguous area, with the area being changed in size depending on conditions. When land use within that area becomes more favourable, the area grows until it becomes the predominant land use. Comparing Subject 4 with the agent, the general sampling strategies are the same, but the agent tended to grow the size of the sample area more quickly in the initial stages, which explains the divergence in land use allocations during the first 10 rounds of the game. When conditions change (rounds 9 to 11), both the subject and agent respond fairly promptly by switching the predominant land use choice. The agent is quicker to respond, perhaps because more cells are being monitored, making the signal that things are changing stronger. In the later rounds (21 to 30) both the subject and agent begin to respond to the sudden shift in payoff reasonably quickly. The subject, however makes a faster transition to the alternative use, while the agent (on average) appears not to respond as quickly.

Another important piece of information within the graph is the standard deviation. In the latter rounds there is a marked increase in deviation of simulated land use. Looking at the use trends on individual simulation runs (Appendix F for data), it became apparent that the deviations were related to differences in response time. When the agent was quick to respond, a similar trend to that of the subject was observed: the number of cells assigned to dark land use plummeted. However, in cases where the agent did not ‘notice’ changes in the price of the alternative use (for example runs 3, 5, 7 and 9), response times were much longer. While most trends eventually began to fall, runs #5 and #9 did not. In those cases the agent had committed all land use to dark, and the resulting lack of information on the state of the alternative use meant that there was no transition to the more profitable light land use. Looking at the narratives produced during rounds 5 and 9, the agent is simply satisfied with the current situation and as a result does not attempt to test the alternative use. Contrasting this with runs in which the agent responded strongly to the change in profitability, (for example runs 2, 7 and 8) the narratives show that the agent was either responding to the obvious difference in payoff between the two land uses, or—in the case of #2—was the result of pro-active
behaviour.

So if over-committing on one particular use was the main cause of the deviation in the final rounds, why did the subject not show any signs of being slow to respond? Looking at the behaviour in Game 1, it is evident that the subject was prepared to commit all cells to one use. For example in rounds 2, 7, 9, 17, and most of rounds 21 to 30. Because the agent was trained from this behaviour, the tendency to commit all cells to one use was programmed in, and was to be expected. The subject perhaps learned from mistakes in the first game, leading to a more cautious approach in the second game. As a result it seems possible that the inaccuracy in the model is caused by change in the subject’s behaviour due to learning.

Looking at the chi-square statistic, the data yields \( P \approx 0.897 \) thus \( P \geq \alpha \), so we accept \( H_0 \). Although the fit is not as good as in the comparison of performance, it is still comfortably within the 95% confidence level, indicating that the observed data could have been derived from a model run.

### 5.4.5.9 Subject 4: Spatial Land Use Pattern

Moving on to the spatial analysis of land use selection, it was decided to break it down into three stages. The reason for this is that the changes in conditions between first, second and third stages mean that the spatial patterns produced should be different in each stage.

The raster diagrams shown in figures 5.14, 5.15 and 5.16, illustrate the total number of times each cell was assigned to dark land use over the relevant period. The raster on the left shows the use patterns recorded from the subject, and the right shows those from the agent. The agent rasters were generated by taking the average number of steps each cell was assigned to dark over the 10 runs (again for the relevant period).

At first glance, the patterns generated by the subject and the agent during rounds 1 to 10 (Figure 5.14) look markedly different. As was observed in the temporal data, the agent clearly assigns the cells to the dark use more often. As was explained earlier, this was a result of the agent tending to grow the size of the sample area more regularly, while not often shrinking it. The same behaviour was recorded from the original subject in Game 1.
Figure 5.14: Number of rounds on dark land use: real vs simulated - rounds 1 to 10

Figure 5.15: Number of rounds on dark land use: real vs simulated - rounds 11 to 20
Another obvious difference is in the location of the sample area. The subject this time chose to start with a sample area in the centre, while the agent chose the top left corner. The agent was hard-coded to start with an area in the top-left at the start of the game since it is exactly what the subject did in Game 1. No other data was available for alternative behaviours at the beginning of the game. Although it is not explained in the narratives, the reason the subject initiated the sample area in the centre of the land area may well have been a result of information learned from the previous game. The spatial pattern in Game 1 indeed makes cells assigned to dark use near the centre, more profitable than those assigned to dark use around the edges.

Although these patterns show obvious dissimilarities in the actions taken by the subject and the agent during the earlier rounds, they also show that the general behaviour is the same. Both the subject and the agent assign an area of cells to the dark land use, and then experiment by sampling neighbouring cells, changing the size and shape of the test area.

In the mid stages of the game, the patterns generated by the agent and subject appear to be in fairly good agreement. Both the agent and subject recognise the areas which give the light cells best payoff. Those cells are then used as sample points when land use is predominantly assigned to dark. Because the subject preferred to use a single sample area, there is a strong preference towards the top-right corner. The top-right has no advantage over bottom-left, and so the agent showed no bias towards either. The reason both areas show about the same level of sampling on light is because the data is the average taken from 10 runs. Even though individual runs showed bias towards a
particular corner, the aggregated data averages this out.

The latter rounds (10 to 20) again show a similar story. At this point both the agent and subject are transitioning from dark to light, tending to switch the top-right and bottom-left sooner, and leaving the other corners assigned to dark longer. Again, there is an obvious bias for a single corner in the subject’s land use for the same reason as described above.

Looking at the statistical correlation with the underlying spatial pattern in revenue (Figure 5.17), the agent’s ability to follow the pattern is clearly visible. At the beginning of the simulation the agent by chance, has been hard-coded to select a pattern with reasonable correlation with the spatial revenue pattern. By sticking to the same general pattern over the rest of the simulation the agent is assured to maintain a certain level of spatial correlation.

By contrast, the subject starts with a pattern centred on the middle of the area - a good strategy for the first game, but no advantage in this one. The subject sticks with this general pattern, growing/morphing it as before. As the game proceeds up to and beyond round 10, the subject appears to begin to recognise the spatial revenue pattern. The correlation plot clearly illustrates this. It also seems to show that the subject has been generally better at taking advantage of the spatial pattern, while the agent slightly lags behind in the later rounds.

The chi-square statistic is found to be $P \approx 0.000$ thus $P < \alpha$ meaning $H_0$ must be rejected. It is not possible to say that the observed data may have been derived from the model with at least a 95% confidence level. This is largely caused by the difference
in initial patterns adopted by the subject and agent. It resulted in a large difference in spatial correlation during the first 10 rounds of the game. Like the subject, the agent is able to maintain a recognised pattern, but less effectively than the subject. The low standard deviation in the agent’s simulation runs shows that while it is not as effective, it is consistent in maintaining a correlation with the spatial revenue pattern.

5.4.5.10 Subject 4: Narratives

Looking at the narratives, how similar is the reasoning underlying the behaviour? The narratives produced by the subject during Game 2 are presented in Table 5.11, while the narratives generated by the agent during Run #2 of Game 2 are presented in Table 5.12. Narratives from Run #2 were chosen for comparison, because during this run the agent appeared to have the most similar land use choices to those of the subject.

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Starting off with dark squares in the middle slight grouped together</td>
</tr>
<tr>
<td>2</td>
<td>leaving them the same to see what happens</td>
</tr>
<tr>
<td>3</td>
<td>light squares seem to be earning more money but everything seems to be staying the same so are going to leave the landuse the same</td>
</tr>
<tr>
<td>4</td>
<td>leaving it the same - earning the same money for the previous two rounds</td>
</tr>
<tr>
<td>5</td>
<td>ok going to change landuse of c2 to see if changing to light increases profits</td>
</tr>
<tr>
<td>6</td>
<td>it does increase profit so will change c4 to light as well</td>
</tr>
<tr>
<td>7</td>
<td>changing d3 to light as light landuse is earning more money - doing this slowly as i dont want to put the whole landuse into light in case it crashes or something</td>
</tr>
<tr>
<td>8</td>
<td>leaving it the same - dont want it all light landuse</td>
</tr>
<tr>
<td>9</td>
<td>same as last round</td>
</tr>
<tr>
<td>10</td>
<td>changing b2 to dark landuse as i dont want it all to be the same landuse incase something bad happens</td>
</tr>
<tr>
<td>11</td>
<td>changing six to dark (around b2) more to dark landuse as light seems to be losing a little bit of money</td>
</tr>
<tr>
<td>12</td>
<td>ok changing more of the light squares to dark as they are losing lots of money - changing the ten bottom squares</td>
</tr>
<tr>
<td>13</td>
<td>changing a couple more to dark (c4, c5) again dont want all to be dark, also changing e1 to light as its earning the least amount of money</td>
</tr>
<tr>
<td>14</td>
<td>leaving the same - dont want all to be dark squares</td>
</tr>
<tr>
<td>15</td>
<td>the squares dont see to be changing much - going to change e1 to see if it increase the profit</td>
</tr>
<tr>
<td>16</td>
<td>leaving the same - again dont want to put everything in one landuse</td>
</tr>
<tr>
<td>17</td>
<td>[NONE]</td>
</tr>
<tr>
<td>18</td>
<td>[NONE]</td>
</tr>
<tr>
<td>19</td>
<td>going to change b4 to see if it improves profit</td>
</tr>
</tbody>
</table>
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Table 5.11: Recorded narratives from Subject 4 - Game 2

During the first transition period near Round 10, the subject’s reasoning for changing to the alternative use is:

“changing six to dark (around b2) more to dark landuse as light seems to be losing a little bit of money”

While the agent produces:

“changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A2, A3, A4, B2, B3, B4, C0, C1, C2, C3, C4, D0, D1, D2, D3, D4, E0, E1, E2, E3, E4”

Although the wording is different, the general reason for the changes is the same in both.

During the second transition period near Round 20, the subject says:

“light squares see to be doing better - changing the squares around the two light ones to light use to improve profit”

And the agent says:

“losing money on all the dark areas so changing A2, B2, C0, C1, C2, C3, C4, D2, E2 to light as areas close by are doing better”
Here both the subject and the agent recognise that there is opportunity to make profit on the light cells, and both make a reference to proximity. This causes the transition to take place by growing the sample area. So again, the behaviours and underlying reasoning appear to be the same.

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>change squares A2, B2, C0, C1, C2 to see if it is affected by landuse of higher revenue close by</td>
</tr>
<tr>
<td>3</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>4</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>5</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>6</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>7</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>8</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>9</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>10</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A2, A3, A4, B2, B3, B4, C0, C1, C2, C3, C4, D0, D1, D2, D3, D4, E0, E1, E2, E3, E4</td>
</tr>
<tr>
<td>11</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A4, E0</td>
</tr>
<tr>
<td>12</td>
<td>going to change A4, E0 to land use dark so see if close association to areas doing better helps</td>
</tr>
<tr>
<td>13</td>
<td>change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>14</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>15</td>
<td>Going to change the landuse of A4, E0 as making the least money</td>
</tr>
<tr>
<td>16</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>17</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>18</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>19</td>
<td>change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>20</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>21</td>
<td>changing landuse of A3, B3, B4, D0, D1, E1 to see if it will increase profits</td>
</tr>
<tr>
<td>22</td>
<td>losing money on all the dark areas so changing A2, B2, C0, C1, C2, C3, C4, D2, E2 to light as areas close by are doing better</td>
</tr>
<tr>
<td>23</td>
<td>losing money on all the dark areas so changing A1, B0, B1, D3, D4, E3 to light as areas close by are doing better</td>
</tr>
<tr>
<td>24</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>25</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>26</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>27</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>28</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>29</td>
<td>Going to change the landuse of A0, E4 as making the least money</td>
</tr>
</tbody>
</table>
Although the narratives seem to be similar when the behaviour is similar, the agent also produced behaviour which was very different to the subject’s. Specifically during runs #4 and #6. In the former, the agent did not really make a marked transition to dark land use during the mid period (as the subject did). Looking at the narratives during these mid-stage rounds, the agent seems content with the current situation, even though some cells are assigned to the alternative use and are clearly making more money. Looking back to the subject’s behaviour during the first game, during the early rounds a similar situation exists. For a large part of the early stage the predominant use is on light, despite the fact that those assigned to dark are doing much better. The subject, however, appears content with the situation because the cells of the alternate use are still making an acceptable profit. The subject would prefer to accept a loss in order to monitor the changes over time, than switching to the alternate use. This aspect of the subject’s behaviour during Game 1 is simply being echoed by the agent in Game 2.

The behaviour in Run #6 shows some fairly abrupt transitions from light to dark and back again. These kinds of behaviours were not observed in the subject during Game 2, but clues may be found as to why they are being expressed by looking at the subject’s behaviour during Game 1. During this game, the subject expresses the behaviour of sampling different sized areas as a proactive bid to increase profits. It happens in rounds 6, 25 and 29. In all but Round 6 the move proves to be unsuccessful, prompting the agent to return the majority of cells to the original use. Because these proactive behaviours are not initiated by any measurable changes in the simulation environment, they can only be assumed to occur as random events. As such they may happen at any time within the context they normally occur in. Looking back to the agent’s narratives in Run #6, the first time this behaviour is observed is in Round 10. The agent quickly realises it has not had the desired effect and switched most back.

5.4.6 Conclusion

This first stage of research and set of experiments involved the development of a methodology for elicitation of human decision making behaviour and encoding into
an artificial agent model. Starting from just a concept, guided by similar experiments from the literature, the initial pilot study demonstrated the feasibility of the methodology, while also highlighting many areas for improvement. The methodology was scaled up and carried out with a number of subjects during a second round of experiments. It involved a more challenging scenario for the subjects, along with a more rigorous validation phase, cross-validating using independent data-sets. The validation done during the final stages showed that more needed to be done to fine-tune the agent models produced. The simulated agent produced in the second round of experiments was successful in recreating some crucial behavioural patterns. This suggests that the methodology will potentially be able to provide good results, providing large enough data sets are used in constructing the artificial agents.
Chapter 6

Case Study 2: Participatory Simulation of Dairy Farming

This chapter documents a case study used to test the feasibility of applying the methodology to a real human decision making problem. The methodology itself is discussed in more detail in Chapter 4. The aim of the case study was to assess the effectiveness of applying the participatory simulation technique to measure decision making behaviour in a realistic environmental scenario. It would specifically examine the practical implications of (1) constructing a complex simulated decision environment; (2) using such an environment to carry out participatory simulations and (3) how easily the data can be converted into a form usable within a BDI agent model.

The case study applied the methodology in a Scottish dairy farming decision environment. This was to ensure that the methodology is not just applicable in highly controlled and abstract decision problems, but also capable of dealing with the practical issues of a real and complex decision environment – the sort of environment which may be of interest to policy makers.

In order to carry out the feasibility assessment, the study employed the empirical aspects of the methodology described in Chapter 4. This study was carried out in three phases: (1) building a simulated environment; (2) eliciting decision making behaviour via participatory simulations; and (3) interpreting the narratives to construct a complete agent schema.
In phase (1) existing models of crop and pasture growth, soil nutrient dynamics, cow population and cow digestion were coupled together in a spatial environment. The environment was configured with vector maps from an existing dairy farm and driven by market and weather data. The market and weather data was generated by a stochastic algorithm calibrated with past market and weather data for the area to ensure fluctuations of a realistic nature.

Phase (2) involved meeting with three dairy farmers in two sessions. The first introduced the simulated dairy model to ensure they were familiar with it. The second, longer session involved each farmer managing the simulated dairy farm on a weekly basis for a period of 10 simulated years.

In the final phase (3), data collected during the participatory simulation experiments was analysed to construct an agent schema. During the process the narratives were assessed and ambiguities/omissions were noted. Deficiencies within the data were used to formulate a set of follow-up questions.

Justification for following the participatory simulation approach, as opposed to using direct observation or interviews is detailed in Chapter 4.

### 6.1 Construction of a Simulated Dairy Farm

In order to carry out participatory simulations with dairy farmers, it was necessary to prepare an artificial dairy farm as the simulation platform. The platform would allow the dairy farmers to carry out the kind of dairy farming tasks typically involved in running their actual farm, encouraging deliberation over the same issues involved in real dairy farming. In order to prepare the simulation platform, either an existing dairy farm simulator would need to be adapted to satisfy the needs of the project, or—if no appropriate implementations were already available—a completely new simulation platform would need to be implemented from scratch. It should be noted that for a complex domain such as dairy farming the construction of a simulation platform to replicate the decision making environment forms a significant portion of the effort involved in the methodology.
6.1.1 Existing Whole Dairy Farm Models

In the first instance several existing dairy farm simulators were assessed with a view to making alterations to meet the project’s goals, but it eventually transpired that none of the systems contained all the necessary components to make use of the model as a whole. Instead components from several models were cherry picked based on their suitability. The following whole farm models1 were considered:

1. **DyNoFlo** - (Cabrera et al., 2007, 2005, 2006; Cabrera, 2004) - This ‘whole farm’ model was empirically grounded in Florida, USA. Its focus is on the management of farm manure and the re-use of its nitrogen content in growing crops. It also simulates weather and climate; cereal crop and pasture growth (corn, wheat and grass); livestock foraging, population and waste management; and also farm economics. Although it is implemented as a spreadsheet, using macros for program logic it is a fairly complex and comprehensive farm model. The cow population component uses a Markov model to allow simulation of heterogeneity in the cow population, without the use of an individual-based model. Using this approach the computational complexity of the model is not related to herd size, but instead related to the number of characteristics represented, and the granularity at which these characteristics are modelled. In this case, the characteristics represented are cow age, months in pregnancy, months in milk and lactation stage. Probabilistic transition rules govern the numbers of animals in each state, moving animals into subsequent states or out of the model when death or culling occurs.

2. **DairyWise** - (Schils et al., 2007b,a; Haan et al., 2007) - This model is heavily based on empirical measurements of a Dutch farm. It simulates the growth of grass and wheat, but the growth rates are not influenced by weather. The model also simulates cow intake and defecation, as well as leaching of nitrates out of the topsoil caused by rainfall. The equations used in the model are documented in Haan et al. (2007), but later attempts to implement the equations revealed that they contained serious errors and ambiguities. They caused the model to become numerically unstable, and implementation could not progress without resolution to these problems.

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1Here, the term ‘whole farm model’ describes a model which includes all the key aspects of a dairy farm, including: crop and pasture growth; livestock grazing, feeding, digestion; milk and manure production; finance, markets and government incentives.
3. **SEPATO U** - (Cros et al., 2003, 2004; Parsons et al., 2001; Duru et al., 2007) - A cow foraging and pasture growth model with specific focus on cow digestion and energy requirements. The model is designed to test the feasibility of different feeding and grazing regimes to assess their efficiency in milk production. The pasture growth model is driven by a basic soil sub-model which includes Nitrogen and water availability. This allows use of manure and fertiliser spreading as a management parameter. Changes in rainfall and solar radiation levels affect the growth rate of pastures.

4. **FASSET** - (Berntsen et al., 2003, 2006) - Another whole farm model simulating livestock, crop growth and nitrate leaching. The equations detailing the model are contained in a Danish paper by Jacobsen et al. (1998) but it was not possible to gain access to it.

5. **IFSM** - (Rotz et al., 2007, 1989, 1999) - Another whole farm dairy model, but no public access to the equations and implementation details are available.

6. **Colno et al. (2002)** - A dairy farm model simulating the effect of rotational grazing. Includes a maize and grass growth model, but not any other cereal crops. Because the equations and description for the growth model were in French, it was not possible to implement this model.

7. **Neal et al. (2006)** - An Australian dairy farm model with a focus on the economies of forage choice. The goal is to find the most efficient combination of forage crops to use in a dairy farming enterprise. This model makes wide use of empirical data in its calibration. A model such as this, that makes extensive use of empirical measurements is fine, so long as the measurements were taken from a location with similar characteristics (climate, soil types and vegetation for example). With its location in a very hot and dry climate, the characteristics of this model’s calibrated location were considered too dissimilar to the Scottish Lowlands for use in this project.

8. **Vayssieres et al. (2007)** - A whole-farm dairying model used in a farmer decision making study. On the surface this model is a good candidate because of its use in a similar study. However on further investigation it turned out that it would not be possible to access the details of the crop growth model because they are only available in a French language paper by R. Jarrige (1988) entitled “Alimentation des bovins, ovins, caprins”.
Of these existing models attempts were made to implement DyNoFlo, DairyWise and SEPATOU with varying success. The implementation of DairyWise was abandoned because many of the model’s equations contained syntactic and possibly semantic errors resulting in numerical instability on testing. Attempts to resolve the issues with the model’s original authors turned out to be fruitless. Other commitments meant they were too busy and unable to investigate the problems.

The attempted implementation of DyNoFlo met with more success, yielding working sub-models. Problems arose with the crop growth model, which was not documented in the paper, but made reference to the model it was originally based upon. Eventually it turned out to be too difficult to find enough information to fully develop the crop model. This left a dairy farm simulator with: a cow population model; lactation and waste model; along with simulation of manure nitrogen dynamics.

The most promising implementation was of the SEPATOU model. Its strong areas were a good coupling between pasture growth, foraging, cow digestion, and resulting milk and manure production. Along with these aspects it also accounted for feeding of alternative forage crops, making use of standard fill and energy units to allow for any feeds for which these values are known to be included. It also included a very basic soil sub-model which simulated changes in nitrate levels and soil water content, but did not include any effects of leaching - an important management variable in dairy farming. As well as leaching, the other main component missing was modelling of cereal crop growth. The use of cereal crops as a forage supplement is common practice amongst Scottish dairy farmers, and was deemed a necessary part of the simulation platform.

6.1.2 Cropping Models

The final required component – cereal crop growth modelling – was not found in any of the whole farm models. As a result, it was necessary to search the literature for models specifically targeting crop growth. With consideration to the intended use, the following selection criteria were used to choose the cropping model:
Important:

1. Driven by easily obtainable input parameters.
2. Ability to represent the application of nitrates in the form of fertiliser or manure.
3. Simulates plant nitrate uptake, and leaching through soil resulting from changes in precipitation levels.
4. Makes use of other weather drivers including at least solar radiation, temperature and precipitation.

Optional but desirable:

5. Represents the effects of cropping management techniques such as rotation and ploughing.
6. A generic set of equations for all crops and grass using the parameter inputs as the basis for variation in their characteristics. This is advantageous because it simplifies the model and creates the flexibility to model a range of crop types, simply by varying input parameters.

The following models were considered:

1. **CropSyst** - (Stockle et al., 2003) - A very comprehensive and widely used crop model. The main problem is that it is deployed as a compiled program, and essentially a ‘black box’ system making tight integration with other models difficult. Some of the key equations used in the model are described, but many are omitted, without which it would not be possible to create a full implementation.

2. **CERES** - (Jones, 1986; Rotz et al., 1999) - Another comprehensive, well documented and widely used crop model. In order to operate, the model requires a large number of empirically measured input parameters. Difficulty in obtaining these parameters meant that the model would not be appropriate for this study.

3. **DSSAT/CROPGRO** - (Jones et al., 2003; Boote et al., 1998; Hoogenboom et al., 1993) - A very interesting cropping model which uses a set of generic equations to describe plant dynamics, with a detailed parameter set allowing the same set of equations to model a wide range of grown crops. The main problem with this model was that it proved difficult to obtain an adequate set of parameters to describe the growth dynamics of wheat and maize grown in the Scottish Lowlands.

4. **SOILN** - (Bergstrom et al., 1991; Eckersten and Jansson, 1991; McGechan and
5. **SUNDIAL** - *(Bradbury et al., 1993)* - A cropping model focusing on detailed representation of the flows of Nitrogen through the soil/plant system. In order to be properly calibrated, the model requires records of soil characteristics for the site being modelled. Because of the difficulty in obtaining these measurements it was decided the model would not be appropriate.

6. **STICS** - *(Brisson et al., 2003, 1998)* - This model is fairly well grounded in theory, and is focused on a simple design with a smaller number of easy-to-establish parameters. It is described by the author as an ‘engineering’ model and as such is designed to be easy to calibrate. The model itself uses the same set of generic equations to model the growth of a range of cereal crops, using the input parameters to model the behaviour of different crop types. Parameter sets characterising wheat and maize are available. The layered soil sub-model simulates the infiltration, leaching and production of nitrates from decaying plant matter. The flow of nitrates is governed by the movement of water from rainfall or irrigation through the soil profile. This allows it to represent water availability to plants and the effect of high levels of rainfall in leaching nutrients out of the soil. The layered approach means that plant rooting during early growth, and turning of the soil through ploughing are also represented. By focusing on simplifying the parameter set, the model simulates the right level of detail, while allowing easy integration with other sub-models.

After the initial analysis it was decided that STICS would be an appropriate model for representing both crop growth and soil water and nitrogen dynamics.

In order to simulate all required aspects of the dairy farming system the following final selection was made. (1) DyNoFlo for the cow population model. (2) SEPATOU for pasture growth; cow foraging, feeding and digestion; milk and manure production. (3) STICS to simulate soil water and nitrogen dynamics, nitrate leaching, and cereal crop growth.

As well as models describing crop and animal dynamics, the simulation platform also required: a farm mapping system to allow spatial management of crops and grazing;
market and weather data to drive the sub-models; and finally a user friendly interface to manage farm tasks and finance.

Figure 6.1: Conceptual design of the dairy farm model

6.1.3 Coupling the Internal Models

Stand alone versions of the three constituent models were first implemented and tested before any attempts to couple them together were made.

Figure 6.1 shows the dairy farm model’s conceptual design. Arrows indicate material flows between the various model components. Black boxes show where sub-models implemented from the literature were used, and how they fit into the rest of the system.

The majority of coupling involved transferring quantities between sub-models and other components of the simulation platform. During the process of coupling, great care was made to ensure that units and semantics of the quantities transferred were common across both sides of the coupling, or that appropriate unit conversions took place where this was not the case. The most complicated coupling occurred at the
interface between the STICS soil sub-model and the SEPATOU pasture model. It involved replacing the basic SEPATOU soil sub-model with the more in-depth STICS soil sub-model.

Both the STICS soil model and the SEPATOU soil model use a generic nitrogen stress index whose value ranges between 0 for maximum stress and 1 for no stress. For soil water, again both models make use of stress indices, but the complication is that SEPATOU uses a single index based on the ratio of actual transpiration to maximal transpiration, while STICS uses an index based on transpiration and another based on moisture availability in the soil. Instead of only using the transpiration based index from STICS, it was decided to combine both the transpiration and soil water availability index to provide a better index for the SEPATOU growth model.

Nitrogen and water stress are the main variables required by the SEPATOU pasture model, but the STICS soil model requires a number of variables from the vegetation model in order to operate. They include LAI (leaf area index); plant mass; expected plant growth in nonrestrictive conditions; rooting depth, and layer-by-layer rooting density. Most quantities such as LAI, plant mass and expected growth were readily available in the existing SEPATOU model. However, the rooting system is not represented within SEPATOU, so implementing it involved coupling the STICS rooting model with the SEPATOU growth model. It required a number of parameters related to the rooting properties of grass to be investigated. Parameters for three commonly used species of grass were found including Cocksfoot, Rye Grass and Fescue.

Temporal integration of the models was fairly straightforward. The crop and pasture models (STICS and SEPATOU respectively) operate on a daily time-step and the Markov population model (from DyNoFlo) uses a weekly time-step. Agent decision making and the main simulation scheduler also work on a weekly time step. For the cropping, pasture and soil models, each week executes seven consecutive iterations of each of the models, simulating cow grazing for the chosen number of cows for that week. The agent or human subject then make decisions based on the resulting soil and biomass state at the end of the 7-day period.
6.1.4 Program Design and Scheduling

Figure 6.2 shows a simplified class diagram for the simulation platform, illustrating the main objects in the program and their associations.

The execution schedule starts with the top level Simulation object in the execStep() method. This method then calls the DairyFarm object’s execStep() method to execute the farm’s various model components. Once the call is complete the Simulation object then calls the user interface’s notifyStep() method to indicate that the environment state has changed. Finally the DairyAgent’s notifyStep() method is called to allow the agent to respond to changes and carry out decision tasks for the following week. When
decision tasks have been completed the scheduler in the Simulation object then loops around and calls the execStep() method once again.

When the DairyFarm object receives a call to the execStep() method it first calls the Livestock object’s execWeek() method to update the population model. The execStep() method then uses the updated livestock demographics along with management parameters set by the agent to partition the cows into fields assigned to grazing. The next portion of the method begins a loop to execute for seven iterations - one for each day of that week. Within this loop, another loop calls the execDay() method for the soil and crop models in each field. The CowDigestion execDay method is then called for each cow group within each field to calculate intake through defoliation and consumption of offered supplement. The CowDigestion model then calculates milk yields and manure production for each cow group. Manure produced by grazing cows is deposited straight back into the fields being grazed, while manure produced by confined cows is added to the slurry tank. The final part of the execStep() method then carries out all market transactions which need to take place for the week executed. They include buying of all feeds and fertilisers used; payment of ongoing costs such as veterinary bills and farm rent; and sale of unwanted calves, cull cows and milk produced.

Depending on whether the system is being used in participatory simulation experiments, or to test artificial agent implementations the DairyAgent object may either represent a human subject or an artificial agent model. When the DairyAgent object represents a human subject an appropriate graphical user interface is presented to the subject to allow actions resulting from decisions to be collected. The graphical interface presented to the subject is described in more detail in the following section.

### 6.1.5 User Interface Design

This section details the design of the graphical user interface (GUI) used by experiment participants during the participatory simulation phase. The interface is designed to offer farmers a view of the artificial dairy farm which allows them to carry out familiar dairy farming tasks.

The main principle used to guide the GUI was to ensure that as much information relating to the current state of the model is shown in the main window as possible.
GUI components relating to simulation inputs were made available through buttons and menus, some of which create secondary windows and pop-ups. The reason for this choice was to ensure that users have maximum visibility of the current simulation state, to enable all elements to be taken into consideration during decision formation. Any obscured elements would mean that they may be less likely to be taken into consideration during the decision making process.

Figure 6.3 shows the graphical components within the main simulation window. The purpose of each numbered component is described below:

1. Tool Bar to allow control and more detailed assessment of the farm’s state. The buttons from left to right, top to bottom do the following: buy from market; sell to market; manage feeding budget; manage cow grazing schedule; manage cropping schedule; detailed evaluation of farm performance; move on to next simulation step; move forward through 3 months of simulation time.

2. Visualisation of the simulation time. The progress bar shows the time in which the simulation started, and shows progress towards the simulation end time. The
current date is shown in the centre of the progress bar.

3. Summary of farm’s performance. From left to right, each progress bar shows performance in crop production; livestock breeding and milk production; environmental friendliness; and financial security and growth. A bar growing to the left of centre indicates poor performance and growing to the right indicates good performance.

4. Weather forecast for the next week. Each glyph summarises the expected weather for the labelled week day. Hovering the mouse over any glyph provides the numerical quantities of each of the weather drivers.

5. Tabs to select the map visualisation. Each field can be visualised by:
   - **Crop**: fields coloured by crop-type.
   - **Yield**: expected crop yield in tonnes per hectare.
   - **Water**: water content of top 20cm of soil in percentage saturation.
   - **Nitrates**: nitrate levels in the top 20cm of soil in kilograms of N per hectare.
   - **Leaching**: nitrates leached out of the upper meter of soil over the past week in kilograms N per hectare.

6. Map of the farm area, allowing control over cropping. Right clicking over the map allows users to carry out cropping tasks or assign a cropping schedule to the field. The map interface also allows fields to be managed as groups, and for cropping schedules to be rotated.

7. Graphs of the past year’s market prices for livestock, feeds and milk.

8. Shows the state of the farm stores. The number in the top-right of each store displays its total capacity. The progress bar shows the proportion of storage taken up by each stored product/item.

Detailed information on how the interface operates can be found by looking at the tutorial and manual for the system in appendices G and H.

### 6.2 Participatory Simulation Experiment

The participatory experiment was conducted with three dairy farmers. The procedure involved two sessions. The first session introduced the farmers to the JABLUS dairy farming simulator. At the beginning of the session a presentation was given, along
with a demonstration of the system in order to provide an overview of how the system works. The farmers were then asked to use the simulator to manage a simple dairy farm, in which environmental and market conditions were kept constant. This ensured that the participants could focus on the task of learning to use the interface, without worrying too much about changing conditions.

During the session a few minor issues with the interface were highlighted, along with desirable features. For the second session the system was updated to remove the bugs, along with the addition of some extra features.

The second session took place a few weeks later, giving the participants some time to become familiar with the system. At the beginning of the session, a refresher demonstration was given in order to present a quick overview of the system, in preparation for the experiments. For the experiments themselves the three farmers were each given a separate laptop, and sat together on a communal table to allow interaction and to encourage cooperative and competitive behaviour. This was included because social interaction among farmers can be an important driver of farmer decision making (Barreteau and Bousquet, 2000; Edwards-Jones, 2006). They were all assigned to farm the same dairy farming scenario, lasting for 10 years (on a weekly time-step).

The scenario chosen was based on random fluctuations of weather and market trends, based on a seed value carefully selected to provide good variability in the key market and weather drivers. The seed chosen generated trends which resulted in a constantly changing environment to challenge the subjects.

In order to record decision making they were given three options: (1) using dictaphones for verbal narration; (2) handwriting the narratives; and (3) typing the narratives. All opted for handwriting. When later asked about the reason for this the consensus was that handwriting would be more comfortable and appropriate in a communal situation, as it had been set up. If the experiments had taken place in a more private setting, such as a booth, the recording of verbal narratives would be more appropriate. The handwritten narratives provided after the experiments were typed up verbatim, and are attached in Appendix I.

During the course of the experiments, feedback from the subjects indicated that they found it difficult to concentrate on the task at hand, while also writing down the reasoning behind their decisions. Much of the time a number of convoluted tasks would
be carried out at once, and by the time it came to write down explanatory narratives the reasoning would be partially forgotten. This problem may have been exacerbated by the use of handwriting to log decision narratives. If narratives were spoken rather than written, then expression of decision narratives could occur during task performance (rather than after), reducing the chances of decision reasoning being forgotten. It would also be likely to reduce the cognitive burden of narrative expression, allowing more attention to be focused to the decision making task.

Another problem was that subjects seemed to be overwhelmed by the level of information available in the interface. They would tend to focus on smaller parts of the system, rather than evaluating the state of the farm as a whole. From the outset, efforts were made to avoid this in the user interface design, by summarising farm performance in each farming area (cropping, livestock, finance and environmental friendliness). Perhaps an interface which draws more attention to all of those areas (via pop-up alerts or an overall performance chart) would encourage a wider focus.

The simulation experiment required execution of ten years at a weekly time step. This is a total of over five hundred weeks for the entire simulated period. With so many weeks in which to make decisions, the average time farmers could use in each week was fairly short. It led to a very ‘compressed’ sense of time. The subjects’ consensus was that the kind of decisions farmers make on a weekly basis can be fairly involved. Clicking week after week quickly in succession meant that a large number of important decisions were being made in a relatively short space of time, leaving little time to weigh up the options.

The problems associated with difficulties in making and recording weekly decisions could be alleviated by a reduction in the total simulation time and/or an increase of the real time set aside to carry out the experiments. This would allow more time to deliberate over the week’s decisions and express the reasoning behind them.

Feedback about the farming platform itself revealed that some of the quantities, particularly the market prices, were not entirely realistic and were possibly more representative of past prices. Although some quantities were wrong it was commented that the system was quite comprehensive, and that the majority of the expected components were present.

As a final comment, competition between subjects appeared to provide good motiva-
tion and interest. The subjects often compared strategies and their performance status. Communication among subjects during the experiments may have encouraged the kind of social interaction that is often observed among farmers in reality.

### 6.3 Constructing the Agent Model Schema

The purpose of constructing agent schemata, in the experiment, was to analyse the narratives to create a descriptive agent model capable of being implemented within a BDI framework. The technique used is discussed in detail in Chapter 4. In order to carry out the interpretation, three components were highlighted from the narratives: beliefs, motives and preconditions. They were highlighted in the narratives using a carefully chosen colour scheme and format. Chapter 4 describes this format in detail, while Appendix J shows the interpreted narratives of farmers A and B, with motives highlighted green, preconditions highlighted red, and beliefs highlighted blue. No interpretation was done on the narratives from farmer C because they did not contain enough detail for a usable agent schema.

Once all components had been highlighted, each unique motive was assigned an identifier. This is denoted in square brackets before each motive in the main narrative text. The same was done for beliefs, with the identifier in square brackets appearing after the expressed belief. The identifiers were given a letter prefix to prevent confusion of beliefs (with prefix ‘b’) and motives (with prefix ‘m’). Preconditions do not require identifiers since they are associated with, and dependent on, the motives they relate to. Where the same preconditions were associated with different motives, they were treated as distinct.

In order to construct the agent model schema (see tables below interpreted narratives in Appendix J), each unique motive was placed in a row in the left column of a two column table. Where the same motive was expressed multiple times, all phrases used to express it were also added to that row. In the right-hand column all preconditions identified as causing the motive to be executed are added, with the disjunctive OR keyword separating them. For any beliefs used within the preconditions, the unique identifier was added to ensure that different terminology used to express the same beliefs was not misinterpreted as another belief. Each unique belief used (the ‘belief
During the course of narrative interpretation and construction of the agent schema a number of issues regarding the semantics of the data arose. Many of the issues can be addressed in the first instance by analysing the subject’s actions, recorded during the participatory simulation session. If that is not sufficient to solve the problem, follow-up interviews with the subjects themselves can be used.

### 6.3.1 Issues Relating to Motive Preconditions

An interesting observation from the interpreted narratives is that reference to preconditions relating to environmental state are very sparse at first, with the majority of motives being driven by higher level motives. As the simulation proceeds, participants tended to use more and more information about the environment state to drive decisions. A movement from goal-directed behaviour initially, to a greater proportion of reactive behaviour later on in the simulation. A potential reason for this is that in the initial stages the participants have not had time to observe changes in the environment state to begin reacting to them.

In a number of cases the same motive was executed more than once, but with different justifications given on each occasion. For example, looking at farmer A’s motive m11 in Appendix J, to “buy calved heifers”. It appears eight times in the narratives, and each time a slightly different causative scenario is described. The list of preconditions associated with the motive also contains eight slightly different preconditions causing the motive to be activated. These large sets of preconditions are beneficial to the model because they create a very detailed picture of the exact scenarios in which the motive is executed. The longer or greater the number of times a participatory simulation experiment is done, the more likely it is that the same motive will be activated in different situations. Eventually, the more a motive is repeated in the narrative data, the better confidence a researcher can have that the motive is well described in the model.

Some motives may have parameters associated with them, representing values or quantities. For example, choosing the feed budget has quantities of feed associated with it, or selling animals requires a number of animals to be chosen. Looking at the schemata in Appendix J, all motives with an ‘x’ variable are examples of motives with associated
parameters.

Where parameters are used, the model must find a way to determine this parameter value based on the narratives given and actions made. In a detailed narrative response the parameter values will be explicitly stated, but more often than not they are left out. If this is the case it is necessary to go through the recorded actions in the simulation to find the quantities chosen in each instance the motive was executed. Often the parameter value chosen depends on the scenario which caused the motive to be executed. Eventually the implemented model will need to be able to generate these parameters when a decision is taken. It may do this either by: (1) using a mathematical relationship linking the state of belief variables to the chosen parameter value, or by (2) randomly generating it according to a distribution calibrated to the original subject’s parameter choices.

Some preconditions, instead of relating to current or past state, are expressed in terms of expected future state. The beliefs they depend upon are slightly more complex because they require the agent program to make the same future projections. In simple environments it may well be easy for the agent algorithm to calculate future state, simply by executing its own version of the model into the future state. However, this should be avoided where possible since it takes no account of the methodology used by the subject to make the prediction.

A good example from the narratives was from farmer B, where the following narrative is given:

“Buy 20 calved heifers in preparation for increase in milk price during winter.”

The precondition causing the motive to be executed is a prediction on the winter’s milk prices. Because the model uses a stochastic algorithm to generate future prices, there is no way for the agent to predict the future milk price unless it has access to the algorithm. However, the issue of implementing the agent with such a belief is possible if it is considered that the future projection is most likely made based on a learned pattern from past milk prices. The subject in the experiment has probably seen high milk prices in past winters and has learned that they are likely to be high in future winters. If this was the case then all that would be necessary would be to equip the agent with the knowledge that milk prices are high during the winter period. In any case, where it is not clear how a future projection has been made, follow-up questions
should be used to resolve the issue.

### 6.3.2 Issues Relating to Beliefs

Where beliefs with an associated quantity are maintained a subject may not only refer to the absolute value of the belief, but also to its historic values and how they have changed. When this is the case the resulting agent program must keep a record of the past belief values as far back as is referenced by the original agent. Doing this allows the agent to maintain and use its memory. When this capability is added to the agent it is important to consider the granularity with which the agent stores past values of a particular belief. In general, as a historic value becomes more distant in the past and has been replaced by many more recent values, a human will tend to generalise past values to keep the burden of storage to a minimum, only storing average values over a period, or important jumps or trends in the belief’s value. In the case of more complex use of past belief values, exactly how the agent keeps track of past belief values should be investigated in follow-up questioning.

In addition to storing past values, sometimes future values of a belief are predicted. If this is the case, that specific belief must be encoded in such a way as to facilitate estimation of future value, as discussed previously with future projected preconditions. An example of such a belief is farmer B’s narrative for 05/01/03, with the precondition “allow for young stock n’s entering herd”. Here the belief referenced is the number of young stock, and the reasoning is based on its expected future value.

For most beliefs which relate to environmental state, there is a direct translation between a state variable in the model and the value of the belief. A good example of this is milk price. However, some beliefs relating to the environmental state are sometimes represented in the subject’s reasoning at a higher level than is represented in the environment. A good example appears in both Farmer A and Farmer B’s narratives. Both make reference to a higher level belief of ‘the weather’, applying qualifiers to the belief such as ‘good’ or ‘poor’. The model itself has no generic weather summary, and only represents rainfall, temperature and solar radiation as state variables. During the experiment the subject uses these pieces of weather information to create a higher level summary of the state of the weather. In order for the agent model representing the subject to do the same thing, it requires extra grounding logic which converts the
three weather state variables into a generic weather summary. By analysing the state of the simulation when subjects made reference to good or poor weather it is possible to build up a picture of the kind of weather that the subject describes as such. However, if possible it will be more useful to ask the subject directly during follow-up questions.

Another issue with grounding, which does not necessarily relate to beliefs is how closely the agent’s stated action motives can be translated to an action which the environment supports. Several examples appear in the narratives, where no direct translation to a model action exists. These include:

- “Made blocks [field groups] that gave a variety of sizes & locations on farm” (farmer A)
- “Create 3 central blocks [of grouped fields]” (farmer B)
- “Set cow grazing groups for year ahead.” (farmer B)
- “Set wheat crop plan for block for year.” (farmer B)

All these actions are fairly high-level and complex, composed of a series of simpler actions executed in a specific manner. In order for the agent model to carry out these higher level actions it must be equipped with knowledge of how they are achieved in terms of the actions supported by the model. Using a similar methodology as is used with beliefs, the grounding process for higher level actions may involve asking questions to the subject, or analysing the actions recorded during the participatory simulation experiment.

### 6.3.3 Reasonless Motives

A problem encountered on every study (to various degrees) was that subjects failed to provide explicit reasoning for all decisions expressed. This is despite efforts to stress the requirement for reasoning before participatory simulation experiments. It may be because the reasoning for many motives seems so obvious that stating it in any normal environment would seem overly fastidious. For example when motive m8: “induce small increase in [milk] yield”, was expressed, no explicit reason was given for it. On the surface, it may appear that it is most likely related to improving profitability of the milking operation. However, there may be deeper reasoning behind this, such as a response to better milk prices, or the changing of seasons. If the researcher fills the
holes in the interpreted narratives by making assumptions the model is at risk of being affected by the researcher’s interpretation and may not be a true representation of the decision maker.

When it comes to encoding the agent in BDI form, these reasonless motives must be resolved. If not the BDI engine will not know when they are to be activated. In some cases the motive will be a root-level motive or goal which is permanently active, influencing behaviour. In other cases the motive is driven by another higher level motive, or there are a set of environmental scenarios which cause it to be activated. What ever the case, the reason behind these apparently causeless motives must be sought from the original subject in order to build the running model.

On a number of occasions the only justification expressed for activating a motive was actually just another higher-level motive. Usually the reasoning stops there, with no indication as to why the original causative motive was executed. An example is the narrative expressed by Farmer A on the date 11/03/01: “Bought shed space for 50 to allow expansion”. The primary motive in the narrative is to ‘buy shed space for 50’. This is said to be activated because of the higher level motive to ‘allow expansion’. The problem is that there is no obvious reason given for the motivation to allow for expansion. It may be because livestock prices are falling, or perhaps because there is excess cash to allow for an increase in the size of the farm. Another consideration is that the motive may be a root-level motive which is permanently sought after, so the farmer is always trying to expand the farm. This is probably less likely since there are many situations in which expanding the farm is not beneficial and would be potentially damaging – when in debt for example.

It appears that the situations where higher level motives were being used as justification for lower level ones were one of the main sources of reasonless motives. In order to resolve the cause for execution of these motives a researcher needs to be able to answer the ‘why’ question until either a root-motive is found or an environmental state of affairs is found which causes the motive to be executed. From a philosophical perspective following this approach makes the assumption that we are not capable of completely impulsive behaviour, meaning we cannot suddenly activate a motive without any prompting or being driven by some high level motivational goal. If the model were to allow for this, then reasonless motives would be activated on random occasions, according to some probability. This functionality may be desirable in some
applications, but for applications in explanatory models it is undesirable since it may lead to behaviours exhibited in which the cause can not be explained.

In some situations a reasonless motive expressed may actually turn out to form one of the subject’s goals. These goals do not have a set of preconditions associated with them, and are active permanently, always influencing behaviour. As an example, to ‘maximise profit’ might be an explicitly stated motive. If queried further and asked why the subject wants to maximise profit the response may be something like personal well-being or happiness. Using the ‘why’ question to probe any further is unlikely to achieve any meaningful results since happiness or well-being is probably a goal or root motive.

Because the BDI framework allows for both goal based and reactive reasoning, having root motives poses no significant implementation difficulties. The important thing for a researcher to establish is whether higher level reasonless motives are indeed goals, or whether they are the result of an internal or environmental state. A portion of the questions presented below the agent schemata in Appendix J were created for the purpose of resolving the reasonless motives found within the narratives.

6.4 Future Work

The case study work done up to this point demonstrates the ability of the methodology to create a model schema capable of implementation as a BDI agent, and highlights issues involved in the behaviour elicitation process. Due to time constraints, it was not possible to carry out any further participatory simulation sessions or implement any of the agent schemata as artificial BDI agents. With only one participatory simulation session having been done, the quantity of decision making information in the schema is fairly low. The sparsity of information present means that although encoding the agent into a BDI may be possible, it will be difficult to create a diverse enough set of behaviours to validate the model properly. For future work it would be desirable to carry out a number of participatory simulation experiments with a small group of farmers to extract a large enough quantity of narrative data to create a realistic BDI agent model.
Chapter 7
Discussion

The discussion chapter is organised into two sections. The first gives a re-cap of the overall project by summarising each stage. The summary is presented according to the sequence in which the work was done, rather than following the layout of the thesis. It describes how the problem was discovered, how it was addressed and the challenges met along the way. The second section then discusses the properties of the methodology, specifically looking at its strengths, weaknesses and proposing where it can best be applied.

7.1 Summary of the Project

The project involved the construction and testing of a methodology for empirical measurement of human decision making behaviour. The methodology is designed to be applied to human-environment systems in which human decision making behaviour plays a key role in the overall dynamics of the system. Inspiration for the methodology came from reading literature on the subject of agent-based modelling on human-environment systems (these were predominantly focused on land use change). A key paper by Parker et al. (2003) identified the approach used to model human decision making as a key challenge in this subject domain.

Further reading into the ABM literature—with a specific focus on decision modelling—revealed that a number of ad-hoc techniques were being adopted, but with little refer-
ence to the theoretical basis behind the technique. Because the vast majority of models in this area are empirically-based, it was necessary to find a technique which was both underpinned by accepted theory of human decision making, while also facilitating the use of empirical decision making data. A literature search into developments in psychology and artificial intelligence revealed a popular and promising philosophy called beliefs-desires-intentions. The philosophy, developed by Bratman (1987), has enjoyed much support in the AI community and as a result now has many incarnations as computational architectures (Ingrand et al., 1992; Braubach et al., 2003; Howden et al., 2001). One of the key reasons for the popularity of the BDI architecture was its ability to represent our intuitions about how we reason. This approach based on folk psychology allows a fairly direct route of translation from expressed decision making behaviour to a computational model of it. This process had already been demonstrated in a pioneering study by Norling (2006).

Based on the past success of BDI, and its suitability to the domain, it was decided that BDI would provide the theoretical foundation upon which the artificial agents would be built. The task was then to construct a methodology to demonstrate the use of a BDI architecture in an empirical study of a human-environment system. During the initial literature search for examples of applied agent-based models in human-environment systems, an interesting abstract land-use decision making experiment by Evans et al. (2006) was discovered. The aim of the study was to compare the decision making behaviour of human subjects, with that of a utility maximising computational agent within a highly simplified and abstract land use scenario. The scenario used basic land use decision making concepts, allowing laypersons to be used as experiment subjects. It also meant that any strategies used by both the subjects and the artificial agents would be simple enough to promote a thorough analysis.

Using this abstract scenario, and a technique of participatory simulation with recording of decision narratives, an initial methodology was put together. The methodology was first tested with a pilot study using a single subject. The pilot study proved successful in demonstrating that the methodology was capable of measuring and simulating decision making behaviour. However, not enough data had been collected to measure the accuracy of the agent model. As well as demonstrating its feasibility, the pilot study also highlighted several areas for improvement of the methodology.

With the improvements taken on board, a second larger study was conducted using nine
subjects. This time, two abstract land use scenarios were developed, so that one could be used for developing the agent, while the second was to be used for validation. The two new scenarios slightly increased the challenge by including the effects of spatial heterogeneity, as well as representing non-linear profit trends. During the experiments all subjects provided good quality narrative data, and demonstrated a good spread in performance. Two agents developed from the narratives were tested and validated. The validation highlighted some differences in behaviour between the real and simulated agents. By inspecting the actions and narratives of simulated agents the likely causes of these differences were identified to be (1) effects of learning causing a change in behaviour and (2) too small a sample of narratives used to construct the agents. Despite these problems, the general behaviour of both agents demonstrated a fairly close match with their respective subjects. It is believed that with adequate treatment of the problems found, the methodology can be used to construct plausible models of human decision making.

By this point the methodology had been tested within a simplified, abstract land use scenario. However, it would be necessary to scale-up the methodology to a realistic case study so that its feasibility in a real empirical setting could be tested. The third set of experiments were designed to do exactly this. The domain chosen was Scottish dairy farming, using real dairy farmers as subjects, and a simulated dairy farm as the simulation platform. The simulated dairy farm was designed to simulate the major drivers affecting farmers’ decision making including: cropping, animal husbandry, trading in changing markets, and realistic fluctuations in weather conditions. Using the system, a participatory simulation experiment was carried out, recording the decision making behaviour of the subjects as well as narratives explaining their behaviour. The narratives were interpreted to construct an agent schema capable of being implemented in a BDI agent system.

7.2 Methodology Weaknesses

7.2.1 Capturing Sufficient Data During Elicitation

Being able to gather a sufficient quantity of narratives for effective coding of a BDI agent is the biggest challenge presented by this methodology. Because of the inherent
complexity of human decision making, a great many distinct motives and beliefs are called upon. It is likely that a single participatory simulation session is only going to draw out a small fraction of these. Normally, the kind of decision making being captured for applied agent-based models is focused on a particular decision making task. This means that often, only a narrow portion of a subject’s overall decision making behaviour is being sought, helping to limit the scope of the search. Despite this, an expert in their profession may learn thousands of facts, rules and procedures in order to inform their decision making. In complex domains such as dairy farming, it may take a great number of sessions to elicit an adequate quantity of data to describe their behaviour, taking up a significant amount of a subject’s time. Not only must the subject carry out many decision making tasks, but a period of training is required in order to familiarise the subject with the simulated environment.

It is not just the decision making domain which can create difficulties for elicitation. The simulated environment designed to provoke these behaviours must be wide enough in scope to generate the range of scenarios that the decision maker will deal with in their real environment. The development of the simulation platform itself is an added challenge in the behaviour elicitation process.

Both the construction of the simulated decision making environment and the extensive participatory simulation and interviews required, make elicitation of adequate behaviour in this methodology a significant challenge.

These problems however, are not unique to this methodology. Many knowledge/behaviour elicitation methods share the same problems and can prove difficult to overcome. The obvious reason for this is the depth and complexity of human knowledge and reasoning.

## 7.2.2 Capturing Learning Behaviour

The methodology is capable of capturing static decision making behaviour, but it cannot capture or simulate learning behaviour. It assumes non-adaptation during the participatory simulation and is supposed to provide a ‘snapshot’ of decision making behaviour. In order to capture and simulate the effects of learning, including adaptation of strategies and creation of completely new ones, a more comprehensive elicitation
process is required, while the BDI model needs to be adapted to support these features of adaptation.

### 7.2.3 Aggregating Decision MakingBehaviour

The methodology presented in this project is designed to map the decision making behaviour of an individual, onto a behavioural agent of that specific individual. No mechanism has been provided for aggregating the behaviour of many subjects who fall into a similar behaviour category. Given the complexity and individuality expressed within human decision making behaviour, it could be argued that attempting to aggregate it is likely to result in poor accuracy and over simplification. However, in larger studies involving thousands of decision making agents it would not be feasible to elicit the decision making of every individual. Instead, it may be necessary to analyse the decision making of a smaller representative group. This would enable the construction of categories which generalise the behaviour of agents to approximate to the average or ‘typical’ decision making made within this group. The level to which this generalisation removes distinctive individual characteristics is debatable. Certainly, the greater the number of categories used the less likely this is to happen. Any project adopting this approach however, must acknowledge that it necessarily results in a loss of realism and accuracy.

With this in mind, what sort of approaches could be used within this type of methodology to achieve aggregation? The least effort intensive approach would be to carry out aggregation during the initial elicitation process. This would involve separating the representative group of decision makers into their respective categories and carrying out participatory simulation in groups, so that narratives produced could be discussed and agreed upon by all subjects within each group. This would ensure that a consistent set of narratives would then be available for the interpretation and encoding into a BDI agent.

A slightly more costly approach would be to carry out aggregation during narrative interpretation, to construct a single agent schema using the narratives from all subjects within a particular category. This process would carry out individual participatory simulation experiments as normal. Narratives from all agents within each category would then be compiled together and interpreted as if they came from the same source.
Any contradictory behaviours would need to be carefully identified and addressed during the schematisation stage in order to construct an internally consistent agent. This approach has the advantage of allowing individuals to express their behaviour freely without being constrained by the group dynamics in the first approach. However, the disadvantage of this is that it requires contradictory behaviours to be resolved during interpretation. Because a number of narratives need to be analysed in each step, the approach is also more costly.

The third option is to carry out aggregation at the model level. In this system agents would carry out participatory simulations individually, and the narratives from them would be interpreted into a separate schema for each subject. From these schemata, individual motive objects with their associated preconditions can be constructed in program code. Once all individuals have been encoded in this way, all motives belonging to agents within each category are then combined together, so that overlapping motives with a similar or the same meaning are represented by the same object, with an altered set of preconditions designed to be consistent among all contributing agents. Any outlying motives expressed only by single individuals may then be optionally removed if they do not represent the behaviour of that category. If no categorisation has been done until the development of individual agents, individual agents can be analysed for overlap in order to construct categories. A similar technique of generalisation is often used during software development in order to reduce code redundancy.

This third approach is the most costly in terms of research effort, but has the advantage of allowing category analysis to take place at the model level. It means that instead of allowing the subjects or a subjective interpretation to resolve differences and similarities in behaviour, the code itself can be grouped using software development techniques to ensure that aggregation can occur with minimum loss of behaviour semantics.

7.2.4 Coding Effort

When applied to a realistic case study, the methodology requires a significant coding effort. The main reason for this is that the decision making environment needs to be re-created in silico in order to allow participatory simulation for recording of decision narratives. Without using participatory simulation it is difficult to retrieve and record the necessary behavioural data from the subject, and there is little or no control over
the scenarios used to provoke the behaviour. In addition, if no simulation of the environment under study is made, it is very difficult to then validate any artificial agent built. This is because the artificial agent would not be capable of executing its decision making behaviour without sending actions to, and receiving input from, the real environment under study.

With the purpose of the methodology in mind (use in agent-based models of human-environment systems), it will always be necessary to build a simulation of the environment under study anyway. In fact, building the environment so that a human decision maker can make their decisions within it will help to ensure that the correct aspects are included. Instead of the researcher choosing which aspects an agent may control, a real decision making subject may express to the researchers these aspects important to them, so that the final simulated platform does not neglect any important decision making drivers.

As well as construction of the simulated platform, the methodology requires significant effort in order to translate narratives into an agent model capable of being executed within a simulation. Again, if the goal of the study is to represent human decision makers realistically, then there is no shortcut for this. Human decision making is known to be complex, and so the effort involved in measuring and simulating that behaviour is reflected by that complexity.

In order to reduce coding effort, human decision making behaviour must be abstracted or aggregated. Depending on the goals of the project this may be necessary, but the resulting loss in realism, and its effects within the wider study must be taken into account.

### 7.3 Methodology Strengths

#### 7.3.1 Behaviour Expressed in Written/Spoken Language

During the behaviour elicitation process, subjects use the most intuitive means possible to express their knowledge - spoken or written language. It allows any kind of information to be expressed, and makes few cognitive demands on the subject, so that concentration can be focused on the decision making task at hand. It has the further ad-
vantage that researchers and others can understand the dialogue or narratives to make for easier interpretation and encoding. It also allows the BDI agent to produce dialogue using similar phraseology, so that the behavioural reasoning generated by the agent is also easily understandable.

7.3.2 Direct Translation of Empirical Data Into a Model

The process of translating the input empirical data (narratives) into the final product (a computational agent) is fairly direct, focusing on minimising interpretation error. The process maintains the phraseology used by the subject both within the intermediate agent schema, and also within the agent itself while expressing its behaviour. The main interpretation involved in the encoding process involves grouping of distinct motives and beliefs (during the schematisation phase), and then grounding these motives and beliefs so that they relate to inputs and outputs from the simulated environment. The internal model of the BDI reasoner itself retains a very close relationship to the original narratives collected.

7.3.3 Transparent and Intuitive Agent Reasoning

The BDI Agents produced using this methodology use a reasoning process which is believable and intuitive to understand. Any researcher probing into the reasons as to why certain behaviours are being exhibited can easily look into the specific beliefs, motives and preconditions being used to drive the behaviour. It can provide a clear understanding into which behaviours have a particular effect on the environment and why—giving vital clues as to how policy might affect that behaviour. This is in contrast to other decision making models used in this field based on complex mathematics or ‘black box’ programs which cannot be interrogated. In such models it is difficult to understand the why behind key behaviours affecting the system making it difficult to adjust policy in such a way as to affect that behaviour.
7.4 Applicability of the Methodology

The developed methodology has specifically been designed to be applied in projects where it is necessary to simulate the behaviour of individual decision makers within an agent-based model of their decision making environment. The final case study of the project examined the feasibility of a typical use for the methodology: Modelling the decision making behaviour of farmers within a simulated farming environment.

The sorts of environments which can be used with this methodology are only limited by what can be encoded into a simulated system, taking into account the resources available for the project. Given the nature and level of detail available in the simulated environments produced in the computer games industry today, the range of possible simulated environments is fairly extensive.

Because the methodology elicits data in peoples’ natural communication language, it should in theory be capable of eliciting behaviour from any subjects capable of communication in language. Where the domain is complex and the terminology not understandable by laypersons it will be necessary for the researcher to gain a reasonable level of understanding of the domain under research before interpretation of narratives is possible.

The methodology is ideal for projects which require a realistic representation of decision making within their agent-based models, such as those used by policy makers. It focuses not only on realism, but also transparency, ensuring that simulated behaviours produced are understandable.
Chapter 8

Conclusion

The following list assesses the goals originally set out at the beginning of the thesis to determine if and how they were met, and what challenges and obstacles presented themselves in the process:

1. *Finding a platform for simulation of human decision making, grounded in theory and suitable for empirical research.*

   During the early stages of the research, a search of the literature revealed some techniques which were currently being used to simulate human-like reasoning (also known as naturalistic decision making). Of the theoretical approaches employed in the literature, it was shown that the decision theoretic approaches, relying on ‘perfect rationality’ gave a poor approximation of human behaviour. As a result there is a trend towards models using an alternative theoretical approach based on ‘bounded rationality’. This is regarded by many as a more realistic theory of human decision making. Many approaches can be used to simulate bounded rationality, but of those found, BDI stood out. It is a holistic theory based on folk psychology and had been shown in previous research to be a good representation of human decision making, while also maintaining a strong link with the type of information we reason with. This makes it easier to gather empirical data in a form suitable for encoding into BDI-based agents. This process had already been successfully demonstrated in an earlier PhD research project by Norling (2006). Whether this platform is the best for the task is still up for debate, but based on its growing popularity, and previous success being used for
this purpose, it would appear to be a suitable choice.

2. **Building a methodology for elicitation and simulation of human decision making behaviour.**

   Again, by borrowing some established techniques from the literature, including participatory simulation, protocol analysis, and developing on the narrative interpretation technique proposed by Norling (2008), a methodology was constructed. Through the application of a pilot study the methodology was further improved upon and formalised. Chapter 4 outlines the entire methodology with sufficient detail to be usable in future research projects.

3. **Testing and validating the methodology with real decision makers.**

   After having demonstrated the first use of the methodology in the pilot study, it was then tested in a larger study involving nine subjects. Two agents developed from narratives recorded during these experiments were tested and validated using a number of techniques. These included statistical comparison of decisions made and resulting optimality (both spatial and temporal), as well as a direct comparison of actual behaviour by examining recorded and generated narratives. Although some differences were observed, the general behaviour adopted by both artificial agents was a reasonable match to that of their respective subjects. The conclusion was that with sufficient narratives to use as a training set, the methodology would be capable of reproducing observed behaviour with a good degree of accuracy.

4. **Testing the feasibility of using the methodology in a complex natural environment.**

   Because the initial development and testing of the methodology had been done within the context of a simplified and abstract decision environment it would be necessary to demonstrate that it could be used in a more realistic and complex setting. This was in order to satisfy the original aim of the project. The decision environment chosen would be that of Scottish dairy farming. This decision environment is composed of a number of challenging aspects whose behaviour can be very difficult to predict and control. Some aspects such as weather and market prices are not directly controllable, but need to be managed in a timely and
intelligent manner to be successful. A large portion of the time used in this phase was involved in constructing a simulated dairy farming environment. It involved a thorough review of recent farm modelling projects; liaising with a veterinary researcher and farming specialists; and a significant implementation effort. The resulting simulation platform was then used by real farmers during training sessions and a participatory simulation session. The participants were satisfied that it presented them with an adequate representation of their farming environment to challenge their farming decision making. During the experiments three sets of narratives were produced, two of which were analysed and converted into agent schemata designed to be implemented as BDI agent models.

Because of the effort involved in the initial phase, resources were not available to complete the BDI agent models. This gives mixed results for the feasibility study. The positives are that it was demonstrated that a simulated environment could be constructed, and that it was capable of provoking realistic farming decision making. Again the narratives expressed during the participatory simulation sessions were detailed enough to construct an agent schema with enough behaviour to construct a workable agent. However, the negatives were that the resource costs of carrying out the final development and validation of these agents proved to be too high to be achievable in this project. This confirms one of the main disadvantages of this methodology, highlighted in the previous chapter—its high research cost.

In summary, the first three goals of the project were adequately satisfied, but the third goal was only partially met. The feasibility test was not able to completely confirm or deny the possibility of the methodology’s success. The implementation of a suitable simulation platform and its use with practising dairy farmers confirmed that the participatory simulation approach was indeed feasible. The construction of agent schemata from the data demonstrated that the data from the participatory simulation sessions was rich enough to allow for an agent implementation to be constructed. Time constraints meant that it was not possible to implement the dairy farmer agent schemata as a BDI models, to allow for simulation-based validation. Having implemented and tested agent schemata in the previous case study demonstrated that it is certainly possible from a methodological perspective. Whether the resulting agent implementation would adequately capture the spectrum of dairy farming decision making behaviour is
still an open question.

In terms of future directions for the research, there were a number of specific challenges mentioned in the earlier discussion (Chapter 7). Namely (1) research into the best means of behaviour elicitation to in order to provide a complete set of decision narratives (2) provision for capturing and simulation learning behaviour and (3) aggregating behaviour so that agents representing general behaviour categories can be developed. The use of BDI in empirical projects such as this is still very new and there is still much scope for improvement of the overall methodology used. It is hoped that the specific focus on formalising the methodology details adopted by this project will help to stimulate research into this interdisciplinary domain of empirically-based modelling of human decision making.

Although the desire to simulate our decision making is not new, the research community is constantly producing new theoretical ideas, along with innovative computational techniques, aimed at more realistic simulation of human decision making. As these developments are made, further opportunities for discoveries and innovation in empirically-based human decision modelling will become available, stimulating research (and ultimately progress) in this challenging domain.
Appendix A

Instructions for Abstract Land Use Experiment
Summary of Proceedings

When you arrive in the lab you will be given a paper copy of these instructions, a consent form and a payment receipt form. The consent form needs to be read and signed before you can begin.

You will then be shown to a computer to do the experiment which shouldn't take more than an hour to complete. If you have any problems during the experiment please notify the supervisor.

When you have completed the experiment sign and date the payment form and take it to the supervisor who will arrange payment in cash.

Your Details

When you first run the experiment program you will be presented with the form below.
You must enter all of the following details before you can proceed:

- **Name:** Your forename and surname
- **Matric No:** Your university matriculation number
- **Email:** Any email address we can use to contact you
- **Age:** Your current age (not date of birth)
- **First Language:** Your first language or the language you are most proficient in
- **Course Level:** The type of degree you are working towards
- **Area of Study:** The general field your course belongs to. Biology for example
- **Year of Study:** Your current year of study

If you have problems with any of the details then please ask the supervisor for assistance. When the form has been completed the first practice game will automatically load.

### Experiment Interface

The graphical experiment interface is composed of an upper input panel and a lower output panel. The **input panel** can be further broken down into three parts:

- **Land Use Editor:** this is the square area on the top left. It allows you select from one of two uses for each cell with your mouse. Multiple cells can be assigned to the same use by holding the mouse button down and dragging the mouse over the desired cells. Don't worry about what each land use actually is, just call them dark and light.
- **Reasoning Textfield:** this white text box on the top right allows you to enter the reasoning behind your land use choice. Please remember to include what you are doing and why.
- **Next Round Button:** press this button when you are satisfied with the land use selection and the reasoning provided. Be careful to ensure you are happy before clicking the Next Round button as it is impossible to go back to the previous round. When pressed the model will calculate the revenues you received for each cell and display them, along with other status data on the lower output panel.

**IMPORTANT NOTE:** The success of the experiment primarily depends on the reasoning given behind each land use choice so it is vitally important that you provide as much information about your thinking as possible. You are encouraged to provide a reason for all decisions made, but it is acceptable to leave it blank where the reasoning is exactly the same as the previous round.
2. Reason for Selection

Cell E5 is doing very badly and appears to be doing worse than last round, so I'm going to try an alternate use to see how it performs.

Cell-by-Cell Revenue [pence/100]

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>36.9</td>
<td>20.5</td>
<td>39.2</td>
<td>24.9</td>
<td>59.9</td>
</tr>
<tr>
<td>2</td>
<td>61.0</td>
<td>79.2</td>
<td>94.9</td>
<td>53.6</td>
<td>39.6</td>
</tr>
<tr>
<td>3</td>
<td>25.6</td>
<td>54.1</td>
<td>52.6</td>
<td>71.8</td>
<td>30.2</td>
</tr>
<tr>
<td>4</td>
<td>43.7</td>
<td>64.3</td>
<td>62.3</td>
<td>63.0</td>
<td>60.1</td>
</tr>
<tr>
<td>5</td>
<td>37.2</td>
<td>25.7</td>
<td>95.6</td>
<td>46.7</td>
<td>46.7</td>
</tr>
</tbody>
</table>

Time [round]: 3
Revenue [pence]: 14.58
Game Total [pounds]: 0.437
Bank [pounds]: 0.437

Revenue Trend
The lower **output panel** has three parts:

- **Revenue Grid:** this labeled grid presents you with a cell-by-cell breakdown of revenues received on the last round. The revenues in each cell are displayed in hundredths of a penny, but don't be alarmed by the very small numbers, it all adds up! If the revenue received on a cell has gone up since the last round a + sign will be displayed next to it, and likewise if it has gone down you will see a - sign. The colour of each cell is shaded according to how much revenue was received on it. The colour bar below the grid shows the scale: Red for very low, yellow for average and green for very high.

The diagram below shows how a cell in the revenue grid might change over time.

<table>
<thead>
<tr>
<th>Round</th>
<th>Revenue</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>17.5</td>
<td>The revenue on the cell starts off very low at 17.5 so it is shaded red to indicate this.</td>
</tr>
<tr>
<td>2</td>
<td>44.6 +</td>
<td>The revenue on the cell has increased to 44.6 and it is shaded yellow because this is about average. The + symbol beside the revenue indicates that it has increased since the last round.</td>
</tr>
<tr>
<td>3</td>
<td>89.7 +</td>
<td>The revenue has increased again (to 89.7) so the + sign is shown again. The revenue is now very high so the cell has been shaded green.</td>
</tr>
<tr>
<td>4</td>
<td>44.3 -</td>
<td>This time the revenue has gone down and so a - sign is shown. Because it is now back down to the more modest level of 44.3 the cell has been shaded yellow.</td>
</tr>
</tbody>
</table>

- **Numerical Data:** to the right of the revenue grid four numerical data are displayed. The current round; the total revenue gained on the last round; the total revenue received for the game so far; and the total amount of money in the bank. The bank stores all money received during the experiment. This is the total you will eventually be paid.

- **Revenue Trend:** so that you can keep track of your performance, a graph is displayed at the bottom right. It plots the revenue received on each round against time.

As well as these components, a few other helper items are provided on the interface. At the very top a URL to these instructions is permanently displayed, and at the bottom there is a status bar and game progress indicator.
**Game Details**

Each game takes place on the interface described above. The experiment consists of an initial unpaid practice game, followed by three real paid games.

The **practice game** lasts for 5 rounds and allows you to get familiar with the interface so that you understand how the games work. Don’t worry about your performance here, as nothing is recorded and money raised during this game is not included in your final bank total. You can re-play the practice game as many times as you like until you are satisfied.

The remaining **2 real games** last for between 30 and 40 rounds. You can expect the whole experiment to take anywhere between 30 minutes and over an hour. However, you may take as long as you like playing each game as there is no imposed time limit. A summary dialog will pop up at the end of each game to inform you that the game is complete and display the total revenue raised during the course of the game.

In each game you should **aim** to select the use which you think will gain the most profit for each cell. The economic model which generates the cell revenues is different in each game and includes both a spatial and temporal element.

**When You’re Done**

When the last game is complete a dialog will pop-up displaying a small message and the total amount of money raised during the experiment. At this stage you should let the supervisor know that you are finished and he/she will check the experiment data and arrange payment in cash, along with a receipt.
Appendix B

Abstract Land Use Experiment: XML Agent Model from Pilot Study

<agent xmlns="http://jadex.sourceforge.net/jadex"
xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
xsi:schemaLocation="http://jadex.sourceforge.net/jadex http://jadex.sourceforge.net/jadex-0.94.xsd"
name="Vicci"
package="jablus.agent.evans">
<imports>
  <import>jadex.adapter.fipa.*</import>
  <import>jablus.agent.Agent</import>
  <import>jablus.Parameters</import>
  <import>java.util.Set</import>
  <import>java.util.TreeSet</import>
</imports>
<Capabilities>
  <Capability name="agent" file="jablus/agent/Agent.capability.xml"/>
</Capabilities>
<Beliefs>
  <!-- The agent’s id -->
  <belief name="id" class="Agent">
    <assignto ref="agent.id"/>
    <fact>new Agent($agent.getAgentIdentifier(), Parameters.VICCI_AGENT)</fact>
  </belief>
  <!-- The environment object -->
  <beliefref name="env"/>
<concrete ref="agent.env"/>
</beliefref>

<!-- Owned land cells -->
<belief name="land" class="TreeSet">
  <fact>new TreeSet()</fact>
</belief>

<!-- For scheduling: whether simulation is ready for land use -->
<belief name="land_use_selected" class="boolean">
  <fact>false</fact>
</belief>

<!-- From BDI Narratives (numbers between 0 and 1 use fuzzy logic) -->
<belief name="satisfaction" class="double">
  <fact>0.0</fact>
</belief>
<belief name="curiosity" class="double">
  <fact>1.0</fact>
</belief>
<belief name="uncertainty" class="double">
  <fact>1.0</fact>
</belief>
<belief name="uncertainty_profit" class="double">
  <fact>1.0</fact>
</belief>
<belief name="uncertainty_trend" class="double">
  <fact>1.0</fact>
</belief>
<belief name="uncertainty_change" class="double">
  <fact>1.0</fact>
</belief>
<belief name="risk_level" class="double">
  <fact>0.5</fact>
</belief>
<belief name="best_profit" class="double">
  <fact>0.0</fact>
</belief>
<belief name="last_profit" class="double">
  <fact>0.0</fact>
</belief>
<belief name="strategy" class="int">
  <fact>0</fact>
</belief>
<belief name="current_land_use" class="LandUseScheme">
  <fact>new LandUseScheme(0, 1)</fact>
</belief>
<belief name="previous_good_use" class="int[][]">
  <fact>null</fact>
</belief>
<belief name="previous_good_profit" class="double">
  <fact>0</fact>
</belief>

<!-- qualitative measures -->
<belief name="VERY_HIGH" class="double">
  <fact evaluationmode="static">0.875</fact>
</belief>
<belief name="HIGH" class="double">
  <fact evaluationmode="static">0.75</fact>
</belief>
<belief name="AVERAGE" class="double">
  <fact evaluationmode="static">0.5</fact>
</belief>
<belief name="LOW" class="double">
  <fact evaluationmode="static">0.25</fact>
</belief>
<belief name="VERY_LOW" class="double">
  <fact evaluationmode="static">0.125</fact>
</belief>

<!-- defines what a good profit trend is -->
<belief name="PROFIT_TREND_VERY_GOOD" class="double">
  <fact evaluationmode="static">0.5</fact>
</belief>
<belief name="PROFIT_TREND_GOOD" class="double">
  <fact evaluationmode="static">0.1</fact></belief>
<belief name="PROFIT_TREND_AVERAGE" class="double">
  <fact evaluationmode="static">0.0</fact></belief>
<belief name="PROFIT_TREND_BAD" class="double">
  <fact evaluationmode="static">-0.1</fact></belief>
<belief name="PROFIT_TREND_VERY_BAD" class="double">
  <fact evaluationmode="static">-0.5</fact></belief>
</beliefs>
<goals>
  <achievegoal name="select_land_use_goal">
    <targetcondition>
      $beliefbase.land_use_selected
    </targetcondition>
  </achievegoal>
</goals>
<plans>
  <!-- SATISFY GOALS -->
  <plan name="new_pattern_plan">
    <body>new SelectLandUsePlan(SelectLandUsePlan.NEW_PATTERN_STRATEGY)</body>
    <trigger>
      <goal ref="select_land_use_goal"/>
    </trigger>
    <precondition>
      $beliefbase.curiosity >= $beliefbase.VERY_HIGH
    </precondition>
  </plan>
  <plan name="change_and_compare_plan">
    <body>new SelectLandUsePlan(SelectLandUsePlan.CHANGE_AND_COMPARE_STRATEGY)</body>
    <trigger>
      <goal ref="select_land_use_goal"/>
    </trigger>
    <precondition>
      $beliefbase.uncertainty_change > $beliefbase.HIGH
    </precondition>
  </plan>
  <plan name="await_trend_plan">
    <body>new SelectLandUsePlan(SelectLandUsePlan.AWAIT_TREND_STRATEGY)</body>
    <trigger>
      <goal ref="select_land_use_goal"/>
    </trigger>
    <precondition>
      $beliefbase.uncertainty_change &gt; $beliefbase.HIGH
    </precondition>
  </plan>
</plans>
$beliefbase.uncertainty_trend &gt; $beliefbase.AVERAGE
</precondition>
</plan>

<plan name="return_to_previous_plan">
<body>
new SelectLandUsePlan(SelectLandUsePlan.RETURN_TO_PREVIOUS_STRATEGY)
</body>
<trigger>
<goal ref="select_land_use_goal"/>
</trigger>
<precondition>
$beliefbase.previous_good_use != null
&&
$beliefbase.uncertainty_change &lt;= $beliefbase.AVERAGE
&&
$beliefbase.satisfaction &lt;= $beliefbase.AVERAGE
</precondition>
</plan>

<plan name="maintain_use_plan">
<body>
new SelectLandUsePlan(SelectLandUsePlan.MAINTAIN_USE_STRATEGY)
</body>
<trigger>
<goal ref="select_land_use_goal"/>
</trigger>
<precondition>
$beliefbase.previous_good_use == null
&&
$beliefbase.satisfaction &gt;= $beliefbase.VERY_HIGH
</precondition>
</plan>

<plan name="maintain_best_plan">
<body>
new SelectLandUsePlan(SelectLandUsePlan.MAINTAIN_BEST_STRATEGY)
</body>
</plan>

<!-- REACT TO EVENTS -->
<!-- Initialise agent -->
<plan name="initialise_agent_plan">
<body>
new InitialiseAgentPlan()
</body>
</plan>

<!-- Revise beliefs at the end of the step -->
<plan name="revise_beliefs_plan">
<body>
new ReviseBeliefsPlan()
</body>
</trigger>
<messageevent ref="step_ended_event"/>
</trigger>
</plan>
<!-- Make decisions for this round -->
<plan name="make_decisions_plan">
<body>new MakeDecisionsPlan()</body>
<trigger>
<messageevent ref="start_step_event"/>
</trigger>
</plan>
</plans>
<events>
<messageevent name="step_ended_event" type="fipa" direction="receive" exported="true">
<parameter name="performative" class="String" direction="fixed">
   <value>SFipa.INFORM</value>
</parameter>
<parameter name="content" class="String" direction="fixed">
   <value>"STEP ENDED"</value>
</parameter>
</messageevent>
<messageevent name="start_step_event" type="fipa" direction="receive" exported="true">
<parameter name="performative" class="String" direction="fixed">
   <value>SFipa.INFORM</value>
</parameter>
<parameter name="content" class="String" direction="fixed">
   <value>"START STEP"</value>
</parameter>
</messageevent>
<messageevent name="agent_initialised_event" type="fipa" direction="send">
<parameter name="performative" class="String" direction="fixed">
   <value>SFipa.INFORM</value>
</parameter>
<parameter name="content" class="String" direction="fixed">
   <value>"AGENT INITIALISED"</value>
</parameter>
</messageevent>
<messageevent name="beliefs_revised_event" type="fipa" direction="send">
<parameter name="performative" class="String" direction="fixed">
   <value>SFipa.INFORM</value>
</parameter>
<parameter name="content" class="String" direction="fixed">
   <value>"BELIEFS REVISED"</value>
</parameter>
</messageevent>
<messageevent name="decisions_made_event" type="fipa" direction="send">
  <parameter name="performative" class="String" direction="fixed">
    <value>SFipa.INFORM</value>
  </parameter>
  <parameter name="content" class="String" direction="fixed">
    <value>"DECISIONS MADE"</value>
  </parameter>
</messageevent>
Appendix C

Abstract Land Use Experiment:
Subject Narratives

This appendix contains the narratives expressed by each of the 9 experiment subjects.

C.1 Subject 1

Age: 24
Language: English
StudyLevel: MSc
StudyArea: GIS
StudyYear: 1st
Total Earned: £8.64

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Give each area a surrounding area to thrive in. Chose pattern to make sure no cells bordering the dark were also dark</td>
</tr>
<tr>
<td>2</td>
<td>Same startgey as got good results. Extend to mark cells dark where the growth is least so shade in all four corner cells (A1, A5, E1, E5)</td>
</tr>
<tr>
<td>3</td>
<td>Forgot to do the last instruction so ditto!</td>
</tr>
<tr>
<td>4</td>
<td>Widespread gain but still low. Spreading land use over wide area not working so switching to strategy where i will have one area of dark and one of light. Colour cells a1, a2, b1, b2 dark and the rest light</td>
</tr>
</tbody>
</table>
Appendix C. Abstract Land Use Experiment: Subject Narratives

5 lowest areas are furthest away from dark patch so will make opposing corner dark. (D4, D5, E4, E5). Still going tfor intensive block
6 Too intensive so will reduce to dark areas of only two blocks. Keep A1, A2 and E4 and E5
7 Lowest areas still furthest from dark areas so will try a spread of dark areas across all corners leaving middle free. Change D1, E1 and A5, B5 to dark as well
8 POsitve result so will maintain strategy for one more go
9 still good althopugh will test by colouring the lowest square dark(E2).
10 Reverse to see if the difference is better overall.
11 Not as good and so will put back with corresponding changes in other corners
12 Loss in areas where I have had dark patches in for a while and so will remove corner pieces.
13 Very poor results and stick to strategy of blocks of dark areas. Homogeneity.
14 same reason as last round
15 [NONE]
16 [NONE]
17 Hit plateau so new strategy based on idea to keep areas homogenous. will try random pattern of blobs (three of four cells of dark cells).
18 No joy. Back to original strategy of checkboard
19 [NONE]
20 [NONE]
21 Same as reason before
22 [NONE]
23 [NONE]
24 [NONE]
25 [NONE]
26 [NONE]
27 [NONE]
28 Fluctuates at level lower than strategy before using the corners as bases of three dark cells. Return to this strategy. (dark cells (A1,2,4,5 B1,5,D1,5,E1,2,4,5)
29 [NONE]
30 [NONE]
31 [NONE]
32 [NONE]
33 [NONE]
34 [NONE]
35 [NONE]
36 [NONE]
37 [NONE]
38 [NONE]
39 [NONE]
40 [NONE]
### Table C.1: Recorded narratives from subject 1 - experiment 1

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Areas of dark cells located around the corners. Same strategy as last game</td>
</tr>
<tr>
<td>2</td>
<td>[NONE]</td>
</tr>
<tr>
<td>3</td>
<td>[NONE]</td>
</tr>
<tr>
<td>4</td>
<td>[NONE]</td>
</tr>
<tr>
<td>5</td>
<td>No movement as so change. Try checkerboard strategy</td>
</tr>
<tr>
<td>6</td>
<td>[NONE]</td>
</tr>
<tr>
<td>7</td>
<td>[NONE]</td>
</tr>
<tr>
<td>8</td>
<td>[NONE]</td>
</tr>
<tr>
<td>9</td>
<td>Not changing. Will start with one area in middle of dark. Which will propagate outwards</td>
</tr>
<tr>
<td>10</td>
<td>Propagate outwards to surrounding cells</td>
</tr>
<tr>
<td>11</td>
<td>[NONE]</td>
</tr>
<tr>
<td>12</td>
<td>Big drop around surrounding cells and no change within cells. Return to basic idea with one dark cell in middle of area.</td>
</tr>
<tr>
<td>13</td>
<td>[NONE]</td>
</tr>
<tr>
<td>14</td>
<td>[NONE]</td>
</tr>
<tr>
<td>15</td>
<td>Propogate in random direction (B4)</td>
</tr>
<tr>
<td>16</td>
<td>[NONE]</td>
</tr>
<tr>
<td>17</td>
<td>A propogation resulted in rise in the cell so will try again with cell D2</td>
</tr>
<tr>
<td>18</td>
<td>Same result so will try to propogate from centre to cell B2</td>
</tr>
<tr>
<td>19</td>
<td>Same to cell D4</td>
</tr>
<tr>
<td>20</td>
<td>[NONE]</td>
</tr>
<tr>
<td>21</td>
<td>Propogate further to cell A5</td>
</tr>
<tr>
<td>22</td>
<td>Caused massive peak so will propogate to E1</td>
</tr>
<tr>
<td>23</td>
<td>Caused another peak so propogate to A1</td>
</tr>
<tr>
<td>24</td>
<td>Still positive so propogate to E5</td>
</tr>
<tr>
<td>25</td>
<td>Same strategy but Static growth. Too much and so remove A1</td>
</tr>
<tr>
<td>26</td>
<td>Remove E5 as growth still static</td>
</tr>
<tr>
<td>27</td>
<td>Will change cells with least value (E1 and A5) but still same strategy of keeping a base and growing around that shape (the middle cell)</td>
</tr>
<tr>
<td>28</td>
<td>High values and so keep earning revenue</td>
</tr>
<tr>
<td>29</td>
<td>[NONE]</td>
</tr>
<tr>
<td>30</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>

### Table C.2: Recorded narratives from subject 1 - experiment 2
## C.2 Subject 2

Age: 22  
Language: English  
StudyLevel: PhD  
StudyArea: Geography  
StudyYear: 1st  
Total Earned: £9.75

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>No dark cells selected to see what level of production is for light colours of all cells.</td>
</tr>
<tr>
<td>2</td>
<td>Change the lowest producing cells to dark blue to see if they improve.</td>
</tr>
<tr>
<td>3</td>
<td>[NONE]</td>
</tr>
<tr>
<td>4</td>
<td>[NONE]</td>
</tr>
<tr>
<td>5</td>
<td>[NONE]</td>
</tr>
<tr>
<td>6</td>
<td>Change to light cells as dark cells begining to loose production, see if light cells produce more</td>
</tr>
<tr>
<td>7</td>
<td>Light cells have far lower production so better to have dark cells even though output seems to decline over time</td>
</tr>
<tr>
<td>8</td>
<td>[NONE]</td>
</tr>
<tr>
<td>9</td>
<td>[NONE]</td>
</tr>
<tr>
<td>10</td>
<td>[NONE]</td>
</tr>
<tr>
<td>11</td>
<td>[NONE]</td>
</tr>
<tr>
<td>12</td>
<td>try light cells as middle cell now producing well</td>
</tr>
<tr>
<td>13</td>
<td>Edge cells seem to produce more in dark cell mode, matters less for central cells</td>
</tr>
<tr>
<td>14</td>
<td>[NONE]</td>
</tr>
<tr>
<td>15</td>
<td>[NONE]</td>
</tr>
<tr>
<td>16</td>
<td>[NONE]</td>
</tr>
<tr>
<td>17</td>
<td>Try converting some edge cells to light to see if they improve production.</td>
</tr>
<tr>
<td>18</td>
<td>[NONE]</td>
</tr>
<tr>
<td>19</td>
<td>[NONE]</td>
</tr>
<tr>
<td>20</td>
<td>[NONE]</td>
</tr>
<tr>
<td>21</td>
<td>[NONE]</td>
</tr>
<tr>
<td>22</td>
<td>All cells now seem to produce increasing ammount in Light blue so changing all cells to this format.</td>
</tr>
<tr>
<td>23</td>
<td>Changing edge cells back to dark as produces more when the pattern of production is on a general downward trend.</td>
</tr>
<tr>
<td>24</td>
<td>[NONE]</td>
</tr>
<tr>
<td>25</td>
<td>[NONE]</td>
</tr>
<tr>
<td>26</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>
27 [NONE]
28 Happy to let cells gradually decline in value at current pattern as risks of changing too
29 great.
30 [NONE]
31 Light central cells are on upward trend so will try converting dark cells to improve
32 production.
33 [NONE]
34 [NONE]
35 [NONE]
36 outside cells still performing badly so will try changing them again.
37 [NONE]
38 output seem more variable but can be better with light blue when at edges, will try this
39 change the cells which are on a downward trend, keep other edge cells light blue as
40 they are improving.
41 No changes made, seems just as likely to decrease output as increase it.

Table C.3: Recorded narratives from subject 2 - experiment 1

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
</table>
| 1    | Try half the board in one colour and half in the other to try and establish any spatial
|      | patterns and preferences for dark or light cells. |
| 2    | Dark cells performed poorly compared to light so changed cell colour to all light. |
| 3    | cells A1, A2, B1, B2 are decreasing so will change colour to see if this improves. Other cells are stable or improving so too risky to change. |
| 4    | Dark cells now doing better so put just over half into dark cells, in case this trend changes. Light coloured cells stabilised at comfortable level, so can afford to take more risk. |
| 5    | Change most poorly performing 4 cells back to light green, to see if they improve. Otherwise keep the same. |
| 6    | Keep the same, А1-2, В1-2 stabilising and may begin to drop but still producing well, row C may increase so keep it dark green. |
| 7    | [NONE] |
| 8    | Try and increase production from those cells at 58.3, so will try a change of colour. Production going ok in other cells so will keep the same. |
| 9    | [NONE] |
| 10   | Try changing bottom half of |

Table C.4: Recorded narratives from subject 2 - experiment 2
### C.3 Subject 3

Age: **28**

Language: **Anglais**

StudyLevel: **PhD**

StudyArea: **Informatics**

StudyYear: **Write-up**

Total Earned: **£9.04**

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>None, first round.</td>
</tr>
<tr>
<td>2</td>
<td>Seems one type of land makes more monies, so switching to that.</td>
</tr>
<tr>
<td>3</td>
<td>Rotating the land that has been used the same for two rounds, as the revenue from those has dropped.</td>
</tr>
<tr>
<td>4</td>
<td>Going back to the first type of land as revenues on changed squares dropped significantly.</td>
</tr>
<tr>
<td>5</td>
<td>Changing one square to see the effect. Revenues good elsewhere last round.</td>
</tr>
<tr>
<td>6</td>
<td>Changing the lone square back, as it’s the lowest revenue square.</td>
</tr>
<tr>
<td>7</td>
<td>Try changing all land to opposite type to try to stem falling revenue.</td>
</tr>
<tr>
<td>8</td>
<td>Seems outer cells get lower revenue with light cells so switch those to darker.</td>
</tr>
<tr>
<td>9</td>
<td>Keeping same config as last round to judge effect.</td>
</tr>
<tr>
<td>10</td>
<td>Setting dark outer cells to light to see if this helps.</td>
</tr>
<tr>
<td>11</td>
<td>Switch all but 5 centremost cells to dark, as these seem to perform poorly with light cells.</td>
</tr>
<tr>
<td>12</td>
<td>Go back to just the outer cells being dark</td>
</tr>
<tr>
<td>13</td>
<td>Change corner cells to light, just experimenting.</td>
</tr>
<tr>
<td>14</td>
<td>Again make corner cells dark as revenue fell lots with light cells.</td>
</tr>
<tr>
<td>15</td>
<td>Unchanged from last round.</td>
</tr>
<tr>
<td>16</td>
<td>Change all to light, as it seems this improves over time.</td>
</tr>
<tr>
<td>17</td>
<td>Leave as all light to see how it performs over a few rounds.</td>
</tr>
<tr>
<td>18</td>
<td>Still improving, so no change.</td>
</tr>
<tr>
<td>19</td>
<td>[NONE]</td>
</tr>
<tr>
<td>20</td>
<td>[NONE]</td>
</tr>
<tr>
<td>21</td>
<td>[NONE]</td>
</tr>
<tr>
<td>22</td>
<td>[NONE]</td>
</tr>
<tr>
<td>23</td>
<td>Had a big drop so try switching to all dark cells for a few rounds to see how that performs. Expect it to be poor initially, but improving over time.</td>
</tr>
<tr>
<td>24</td>
<td>Improved a lot, so leaving as-is.</td>
</tr>
<tr>
<td>25</td>
<td>Falling revenue, but leaving as-is for one more round.</td>
</tr>
<tr>
<td>26</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>
27 Switch all to light cells, to see if the land is ‘ready’ to take this type of use again.
28 Try another round with all light cells.
29 Revenue improving again so leaving as-is to see if it continues to improve.
30 Still improving, so leaving as-is.
31 [NONE]
32 Changing corner cells as they’re not performing well.
33 Getting good results for all cells, leaving for one round.
34 Switching some cells near the corners, still good revenue in the centre so can afford to experiment outwith those cells.
35 Revenues OK so leaving as-is.
36 [NONE]
37 Changing all to light cells as these are performing best.
38 Good, growing revenues so leaving same as last time.
39 [NONE]
40 [NONE]

<table>
<thead>
<tr>
<th>Table C.5: Recorded narratives from subject 3 - experiment 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step</td>
</tr>
<tr>
<td>------</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td>6</td>
</tr>
<tr>
<td>7</td>
</tr>
<tr>
<td>8</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>10</td>
</tr>
<tr>
<td>11</td>
</tr>
<tr>
<td>12</td>
</tr>
<tr>
<td>13</td>
</tr>
<tr>
<td>14</td>
</tr>
<tr>
<td>15</td>
</tr>
<tr>
<td>16</td>
</tr>
<tr>
<td>17</td>
</tr>
<tr>
<td>18</td>
</tr>
<tr>
<td>19</td>
</tr>
<tr>
<td>20</td>
</tr>
<tr>
<td>21</td>
</tr>
<tr>
<td>22</td>
</tr>
</tbody>
</table>
Appendix C. Abstract Land Use Experiment: Subject Narratives

23 Forgot to make change last round! Do it this round.
24 Really good revenues on last round, so expand the light coloured cells this time.
25 Really good revenue again, try some more light cells.
26 Change all to light cells, as these are performing very well.
27 Leave same as last round, revenue strong.
28 [NONE]
29 [NONE]
30 [NONE]

Table C.6: Recorded narratives from subject 3 - experiment 2

C.4 Subject 4

Age: 25
Language: English
StudyLevel: PhD
StudyArea: GIS/Geography
StudyYear: 1st
Total Earned: £9.33

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>Leaving them the same as all seem to have started off making ok money</td>
</tr>
<tr>
<td>3</td>
<td>Top left square losing some money - but still making ok money so will leave it.</td>
</tr>
<tr>
<td>4</td>
<td>Going to change the landuse of A5, E1, E5 as making the least money</td>
</tr>
<tr>
<td>5</td>
<td>Going to leave land use the same this round because want to see what happens and even though the top left box is losing money - its only a little bit</td>
</tr>
<tr>
<td>6</td>
<td>Going to change some of the landuse for the top left square (A1, A2, A3) just to see what happens and if this increases revenue</td>
</tr>
<tr>
<td>7</td>
<td>Going to change landuse of A1 back to dark as its the square earning the least amount of money and its going down</td>
</tr>
<tr>
<td>8</td>
<td>Leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>9</td>
<td>Going to change landuse on squares D1 and D5 to landuse dark as they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>10</td>
<td>Changing squares A2, A4, B5, E2, E4 as earning least amount of money</td>
</tr>
<tr>
<td>11</td>
<td>last round was left the same - this round is that reason (sorry conrad)</td>
</tr>
<tr>
<td>12</td>
<td>change squares c3, b3, c2 to landuse light to see if it is affected by landuse of higher revenue close by</td>
</tr>
</tbody>
</table>
Appendix C. Abstract Land Use Experiment: Subject Narratives

13 going to change land use of b2 and c1 as close to other areas doing well
14 leaving the same for this round to observe what happens
15 changed the landuse of the areas b1, d1, b5, d5 as these areas are losing money and are close to areas doing better
16 that last idea didn’t work... going to leave it the same this round
17 changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing a1 a2 a3 a4 e1 e2 e4 e5 - all areas are light landuse
18 leaving the same landuse as the last round
19 leaving same landuse as last round
20 all areas are making money so leaving landuse the same
21 [NONE]
22 [NONE]
23 all landuse went really bad so changing the border to dark landuse as the whole area went to losing money and they are the worst performing areas
24 all areas back to making money so are going to leave landuse the same
25 going to try and change landuse of b2, b4, d2, d4 to dark to see if can increase profit on these areas
26 changing land use of e4, e5 to light to see if can increase profit these are a couple of the areas losing money
27 changing e4 and e5 back to dark as they are not making much money at all
28 leaving the same landuse as last round
29 changing landuse of a1, a2, b1, b2 to see if light landuse will increase profits
30 this didn’t work so will change those four areas back to dark land use
31 leaving areas as the same
32 losing money on all the dark areas so changing b2, b4, d2, d4 to light as areas close by are doing better
33 changing area c1 and c5 to light as areas close by are doing ok
34 that didn’t really work - so are going to change them back to dark land use
35 leaving land use the same
36 losing money on the border area of dark - so going to try changing a1-a3 to landuse light
37 only a3 improved on the last round so going to change c1, c5, and e3 to light and a2 and a4 back to dark
38 going to change b1, b5, d1, d5 to land use light so see if close association to areas doing better helps
39 leaving the same landuse
40 changing a2 a4 land use to light to see if it improves profit

Table C.7: Recorded narratives from subject 4 - experiment 1

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Starting off with dark squares in the middle slight grouped together</td>
</tr>
</tbody>
</table>
leaving them the same to see what happens
light squares seem to be earning more money but everything seems to be staying the same so are going to leave the landuse the same
leaving it the same - earning the same money for the previous two rounds
ok going to change landuse of c2 to see if changing to light increases profits
it does increase profit so will change c4 to light as well
changing d3 to light as light landuse is earning more money - doing this slowly as i dont want to put the whole landuse into light incase it crashes or something
leaving it the same - dont want it all light landuse
same as last round
changing b2 to dark landuse as i dont want it all to be the same landuse incase something bad happens
changing six to dark (around b2) more to dark landuse as light seems to be losing a little bit of money
ok changing more of the light squares to dark as they are losing lots of money - changing the ten bottom squares
changing a couple more to dark (c4, c5) again dont want all to be dark, also changing e1 to light as its earning the least amount of money
leaving the same - dont want all to be dark squares
the squares dont see to be changing much - going to change e1 to see if it increase the profit
leaving the same - again dont want to put everything in one landuse
[NONE]
going to change b4 to see if it improves profit
goingt to change b5 as should improve profit
going to change e1 to light and a4 to dark to see if improves profit
light squares see to be doing better - changing the squares around the two light ones to light use to improve profit
wow - that jumped up a lot!! going to change a few more to light use to improve profit. changing them close to the light use
going to change a few more as profit really seems to be good for the light areas
going to change only a couple more - still dont want to put everything in one colour
going to leave it for this round - dont want to have all light use
[NONE]
going to leave it - dont want it all to be one landuse
[NONE]
change one more to light landuse to see if that improves profit

Table C.8: Recorded narratives from subject 4 - experiment 2
## C.5 Subject 5

Age: **21**
Language: **English**  
StudyLevel: **BSc**  
StudyArea: **Geography**  
StudyYear: **3rd**  
Total Earned: **£9.45**

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>To see what happens when all light</td>
</tr>
<tr>
<td>2</td>
<td>Light did worst around edges, best in the middle, so changed edges to dark</td>
</tr>
<tr>
<td>3</td>
<td>[NONE]</td>
</tr>
<tr>
<td>4</td>
<td>[NONE]</td>
</tr>
<tr>
<td>5</td>
<td>Dark seems to do best</td>
</tr>
<tr>
<td>6</td>
<td>[NONE]</td>
</tr>
<tr>
<td>7</td>
<td>All dark as dark is best</td>
</tr>
<tr>
<td>8</td>
<td>See what happens when light, some light by themselves, some touching other light</td>
</tr>
<tr>
<td>9</td>
<td>Light makes less</td>
</tr>
<tr>
<td>10</td>
<td>[NONE]</td>
</tr>
<tr>
<td>11</td>
<td>Light now makes more</td>
</tr>
<tr>
<td>12</td>
<td>Light makes most in centre</td>
</tr>
<tr>
<td>13</td>
<td>[NONE]</td>
</tr>
<tr>
<td>14</td>
<td>[NONE]</td>
</tr>
<tr>
<td>15</td>
<td>Dark edges making progressively less, now time to change to light</td>
</tr>
<tr>
<td>16</td>
<td>Light edges make less than dark</td>
</tr>
<tr>
<td>17</td>
<td>[NONE]</td>
</tr>
<tr>
<td>18</td>
<td>[NONE]</td>
</tr>
<tr>
<td>19</td>
<td>[NONE]</td>
</tr>
<tr>
<td>20</td>
<td>Light now makes more on edges than dark</td>
</tr>
<tr>
<td>21</td>
<td>[NONE]</td>
</tr>
<tr>
<td>22</td>
<td>[NONE]</td>
</tr>
<tr>
<td>23</td>
<td>Light now makes less on edges, try dark</td>
</tr>
<tr>
<td>24</td>
<td>[NONE]</td>
</tr>
<tr>
<td>25</td>
<td>[NONE]</td>
</tr>
<tr>
<td>26</td>
<td>[NONE]</td>
</tr>
<tr>
<td>27</td>
<td>[NONE]</td>
</tr>
<tr>
<td>28</td>
<td>[NONE]</td>
</tr>
<tr>
<td>29</td>
<td>Dark making most</td>
</tr>
<tr>
<td>30</td>
<td>Dark making slightly less now so see how much light makes</td>
</tr>
<tr>
<td>Step</td>
<td>Narrative</td>
</tr>
<tr>
<td>------</td>
<td>-----------</td>
</tr>
<tr>
<td>1</td>
<td>Stripes to see which colour makes more in different locations</td>
</tr>
<tr>
<td>2</td>
<td>Dark makes biggest least in top right and bottom left, change to light</td>
</tr>
<tr>
<td>3</td>
<td>Dark making loss in C1-5, try light</td>
</tr>
<tr>
<td>4</td>
<td>[NONE]</td>
</tr>
<tr>
<td>5</td>
<td>[NONE]</td>
</tr>
<tr>
<td>6</td>
<td>[NONE]</td>
</tr>
<tr>
<td>7</td>
<td>See which makes most in C3, light not much, try dark</td>
</tr>
<tr>
<td>8</td>
<td>C3 better as light</td>
</tr>
<tr>
<td>9</td>
<td>[NONE]</td>
</tr>
<tr>
<td>10</td>
<td>[NONE]</td>
</tr>
<tr>
<td>11</td>
<td>[NONE]</td>
</tr>
<tr>
<td>12</td>
<td>Light made loss in B1-5-D1-5</td>
</tr>
<tr>
<td>13</td>
<td>Light making loss in A3-5 adn E1-3, try dark, so all dark</td>
</tr>
<tr>
<td>14</td>
<td>[NONE]</td>
</tr>
<tr>
<td>15</td>
<td>No difference, so trying to intersperse light and dark in A3-5 and E1-3</td>
</tr>
<tr>
<td>16</td>
<td>Dark makes slightly more money</td>
</tr>
<tr>
<td>17</td>
<td>Dark A4 and E2 making squares around, such as B5 lose more money</td>
</tr>
<tr>
<td>18</td>
<td>[NONE]</td>
</tr>
<tr>
<td>19</td>
<td>Light A3 and 5 and E1 and 3 making biggest loss, so experimenting with A by making all dark</td>
</tr>
<tr>
<td>20</td>
<td>[NONE]</td>
</tr>
<tr>
<td>21</td>
<td>All dark seems best</td>
</tr>
<tr>
<td>22</td>
<td>Making less in A 5 and E1 so trying light</td>
</tr>
<tr>
<td>23</td>
<td>Light makes lots of money here, trying light in A4 and B5</td>
</tr>
<tr>
<td>24</td>
<td>Light makes most money here, so trying light over A3 B4 C1 C5 D1 D2 E2 E3</td>
</tr>
<tr>
<td>25</td>
<td>Light making most money, trying all light</td>
</tr>
<tr>
<td>26</td>
<td>Light makes most money</td>
</tr>
<tr>
<td>27</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>

Table C.9: Recorded narratives from subject 5 - experiment 1
Appendix C. Abstract Land Use Experiment: Subject Narratives

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>To get a ‘feel’ for what the board does in its default configuration.</td>
</tr>
<tr>
<td>2</td>
<td>To get a ‘feel’ for how constant this is through time I kept everything the same.</td>
</tr>
<tr>
<td>3</td>
<td>[NONE]</td>
</tr>
<tr>
<td>4</td>
<td>I’m now trying to get a feel for how the opposite configuration behaves for the next few steps.</td>
</tr>
<tr>
<td>5</td>
<td>That seemed to go very well so I think I’ll try that again.</td>
</tr>
<tr>
<td>6</td>
<td>Still seems to be going well, so I’ll stick for one more round before I begin some experiments.</td>
</tr>
<tr>
<td>7</td>
<td>That was okay, I think when I see green I’m happy and the entire board is uniformly green. Now I think that this may be because I haven’t introduced any spatial differences. If I change a cell’s use will I ever be able to get back to an all green board? It’s tempting to stay like this for at least one more step.</td>
</tr>
<tr>
<td>8</td>
<td>[NONE]</td>
</tr>
<tr>
<td>9</td>
<td>With each step, the overall revenue is now falling. What happens if I make everything light again. (I’m still trying to get a feel for the system.)</td>
</tr>
<tr>
<td>10</td>
<td>The centre seemed to go up, but the edges are now lower. It’s Good to see that this is a similar configuration to what I had when I first started with an all light board. I can’t remember if the centre was higher or lower then though. I’ll try to change the non green cells and see if I can pull them up a bit.</td>
</tr>
<tr>
<td>11</td>
<td>That worked well. I’ll do that one more time, but I feel the longer I keep the same configuration without introducing changes, the more the profits drop.</td>
</tr>
<tr>
<td>12</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>

Table C.10: Recorded narratives from subject 5 - experiment 2

C.6 Subject 6

Age: 24
Language: English
StudyLevel: PhD
StudyArea: Glaciology
StudyYear: 3rd
Total Earned: £9.01
The centre 9 cells are going up in value, but the edges are slowly dropping. I'll change them back to see how that affects the system.

The centre went up, but the edges when down, which meant overall that didn’t pay off. I’ll change it back to what I know.

Oh dear, the edges are still dropping but the centre is still rising. I’ll try to change the centre back again. I’m tempted to change the centre square, but 41.9 and rising is so close to 49.3 that it doesn’t seem worth it. Each cell seems connected with a surface to the other cells, so my assumption is that if I pull the centre cell down then the other cells around it will also go down, but of course this may not be the case.

Let’s see what happens, the edges are starting to go down a lot now.

Very bad move for the centre. So I’ll change that back again. The middle of each edge is doing better so I’ll make the 3 centre tiles for each edge light. That only leaves the corners dark, so I’ll leave them. Having everything light just seems bland!

That worked, but bland it may have to be as the corners are doing worse than everything else.

That’s a bit better. I’m beginning to feel that at the moment, whenever I introduce a dark cell I start to do worse. I’ll leave it like this for a few rounds unless the values start dropping off drastically. I’m expecting some drop off.

Profits are rising, so why change?

Oh dear. Let’s go all dark now as I’m hoping that then my lowest will be around 24.7, not the highest.

That worked. When I first started, I was in this situation and the value kept going up with each round so I’ll try that again.
Appendix C. Abstract Land Use Experiment: Subject Narratives

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Feeling the ground same as in the previous game.</td>
</tr>
<tr>
<td>2</td>
<td>[NONE]</td>
</tr>
<tr>
<td>3</td>
<td>Now for the other colour</td>
</tr>
<tr>
<td>4</td>
<td>In the last round I visualised a paraboloid surface $x^2y^2$, this time I’m seeing a surface in the shape of a saddle. I’m going to swap the colours in the lower points of the saddle (top right, bottom left) to see what happens.</td>
</tr>
<tr>
<td>5</td>
<td>One more time.</td>
</tr>
<tr>
<td>6</td>
<td>That's evened things out a bit, but what can I do to increase the profits now? All four corners are now maxima in this domain, so I need to change the c row, and column 3. I'm leaving the edges unchanged for now.</td>
</tr>
<tr>
<td>7</td>
<td>That brought the centre up, now I want to bring the middle of each edge up so I'm making those light.</td>
</tr>
<tr>
<td>8</td>
<td>I want to see what happens if I don’t change anything.</td>
</tr>
<tr>
<td>9</td>
<td>[NONE]</td>
</tr>
<tr>
<td>10</td>
<td>Now I want to make the highest earning corners light and see if that increases their value.</td>
</tr>
<tr>
<td>11</td>
<td>No, I'm going back</td>
</tr>
<tr>
<td>12</td>
<td>I'm making all the 39.1 cells dark. This has left me with an entirely dark board.</td>
</tr>
<tr>
<td>13</td>
<td>Changing all cells earning less that 50 to see what happens.</td>
</tr>
<tr>
<td>14</td>
<td>Trying to make it all light to see what happens.</td>
</tr>
<tr>
<td>15</td>
<td>This isn’t good. I’m going to try a stipply pattern to see if that changes things at all. No really reason except that was what I ended up drawing and I didn’t want to swap everything to be uniform again.</td>
</tr>
<tr>
<td>16</td>
<td>[NONE]</td>
</tr>
<tr>
<td>17</td>
<td>[NONE]</td>
</tr>
<tr>
<td>18</td>
<td>[NONE]</td>
</tr>
<tr>
<td>19</td>
<td>Those seem to work. I’m going to get rid of the light green strips, but introduce a light green corner for the cells earning 38.9</td>
</tr>
<tr>
<td>20</td>
<td>[NONE]</td>
</tr>
<tr>
<td>21</td>
<td>The corner cells E1 and A5 are still doing badly. I feel this is forcing me to an all dark board again, which I find a bit boring. Maybe I should simply accept that 77.8 is good and that I can’t get the earning power upto yellow or even green this game.</td>
</tr>
<tr>
<td>22</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>
I'm tempted to attempt to rescue the corner cells again. They bother me so I keep swapping back and forth with the (vain?) hope that something will happen.

So not quite so vain. I'm going to expand to the C row and 3 column.

And now I hope to expand to the remaining squares earning less than 100. i.e. all light.

I'll level off here for now. As I'm near the end I'll just keep clicking unless the profits start dropping badly.

Table C.12: Recorded narratives from subject 6 - experiment 2

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Develop all squares evenly</td>
</tr>
<tr>
<td>2</td>
<td>All squares responded uniformly to the selection, all positive. Continue this process.</td>
</tr>
<tr>
<td>3</td>
<td>All Squares show a decrease. Re-select all to investigate whether this is a blip or not.</td>
</tr>
<tr>
<td>4</td>
<td>Decrease continues. Select only half the field to investigate consequence.</td>
</tr>
<tr>
<td>5</td>
<td>Sudden drop in half of field that is not selected. Decrease still evident in selected half. Select whole field to try to reverse the decline.</td>
</tr>
<tr>
<td>6</td>
<td>Increase seen once again in selected area. Area that has been constantly selected still shows a decline however is still green so will continue with the whole of the field selected.</td>
</tr>
<tr>
<td>7</td>
<td>Decline still evident. Further test cells opened up to monitor the effects of not selected areas. Having the cells all selected seems to show only minimal decreases in revenue when compared with not.</td>
</tr>
<tr>
<td>8</td>
<td>Dramatic decrease in areas not selected. Continue with the selection of all areas (-2 cells) as production still green</td>
</tr>
<tr>
<td>9</td>
<td>Cells not selected respond and show increase. Deselecting more cells to try and stimulate increase. Selected cells still showing minimal decrease</td>
</tr>
</tbody>
</table>

C.7 Subject 7

Age: 27
Language: English
StudyLevel: MSc
StudyArea: Forest Geoscience
StudyYear: 1
Total Earned: £9.86
Appendix C. Abstract Land Use Experiment: Subject Narratives

10 Minimal increase shown in previously selected cells. Decrease continues in selected cells. Decide to let decrease continue until roughly half of scale then deselect and reselect to stimulate growth.

11 Deselect selected areas. Select those not previously selected.

12 Growth seen to be stimulated in some areas, less uniform than before. Selecting the areas that did not show any improvement

13 Selected areas show overall improvement. Keep selected area the same. Deselect any area that showed a drop

14 Selected areas showing a decline. Feel that they might be over exhausted so have deselected most of the grid. Areas of the grid still showing increase. Select areas that are not showing such strong increase

15 Decline shown in areas that have been selected. Begin to suspect that the system needs to ‘recover’ after period of use. Deselect all areas.

16 All areas respond to this. Same strategy for this round.

17 Increase still visible.

18 As previous.

19 [NONE]

20 [NONE]

21 [NONE]

22 All areas still showing increase. No point in attempting to change the strategy

23 All areas crash! disaster. drought most likely. Select entire grid to try and remediate. Leave centre unselected (it wast the most green to observe changes

24 green areas restored. Centre cell shows increase also. Considering deselecting all areas to see if previous patterns of before(1 round deline then steady increase are shown). Or as before keep all selected and accept slow decline, though still showing production? Decide the former.

25 Worse than feared. Centre cell shows increase however all have plummeted. select worse affected areas around outside to try and remediate

26 Increase seen. Centre areas which were not selected still increasing. Decide to stick with selection pattern for another round.

27 Selected areas show decrease. Unselected areas show increase. Deselect all.

28 expected decrease observed. leave all unselected. hope for increase!

29 Increase observed. Continue the strategy

30 [NONE]

31 [NONE]

32 [NONE]

33 [NONE]

34 [NONE]

35 [NONE]

36 increase still observed. Continuing, wary of crash as per last time

37 No point in attempting to change the strategy.

38 [NONE]
Table C.13: Recorded narratives from subject 7 - experiment 1

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Select whole area minus center cell to observe the effect</td>
</tr>
<tr>
<td>2</td>
<td>Decline across the board! Will continue with selection to try and guage effect. Selecting only half the cells.</td>
</tr>
<tr>
<td>3</td>
<td>Selected cells show increase. Remainder of cells show no change (cannot get any worse perhaps?) Deselect all</td>
</tr>
<tr>
<td>4</td>
<td>Increase seen in newly deselected cells. No change in others. Continue with lack of selection to observe</td>
</tr>
<tr>
<td>5</td>
<td>Single cell previously selected showed decline. No change observed in other cells. Select on cell to observe</td>
</tr>
<tr>
<td>6</td>
<td>No change. Selected cell shows improvement. No change in rest. Continue to observe</td>
</tr>
<tr>
<td>7</td>
<td>No change. Select top line to see if some improvement can be stimulated</td>
</tr>
<tr>
<td>8</td>
<td>Increase seen in some cells, decrease in others. Decide to select all cells.</td>
</tr>
<tr>
<td>9</td>
<td>More varied performance. Area seems to be responding in quarters, 2 showing growth. Select two that have increased positively</td>
</tr>
<tr>
<td>10</td>
<td>Areas not selected show increase. Areas selected bomb. Deselect all.</td>
</tr>
<tr>
<td>11</td>
<td>Increase seen uniformly. Leave all not selected, select random squares to monitor</td>
</tr>
<tr>
<td>12</td>
<td>Selected areas show increase. Others sharp decrease. Select all except areas that have responded previous round</td>
</tr>
<tr>
<td>13</td>
<td>All areas respond and increase except those not selected. Continue with strategy</td>
</tr>
<tr>
<td>14</td>
<td>No improvement seen. All areas still poor. Annoying</td>
</tr>
<tr>
<td>15</td>
<td>Random areas deselected to see results.</td>
</tr>
<tr>
<td>16</td>
<td>Areas show decrease. Will continue to observe</td>
</tr>
<tr>
<td>17</td>
<td>All areas stagnant. :(</td>
</tr>
<tr>
<td>18</td>
<td>No improvement seen. Selecting all to max figures. Cannot seem to stimulate growth!</td>
</tr>
<tr>
<td>19</td>
<td>Select areas that are showing values of less than 50.</td>
</tr>
<tr>
<td>20</td>
<td>Decrease in those areas. Continue</td>
</tr>
<tr>
<td>21</td>
<td>No effect observed. Continue</td>
</tr>
<tr>
<td>22</td>
<td>Ah ha! at last. Areas left unselected show increase. Deselect all areas</td>
</tr>
<tr>
<td>23</td>
<td>All areas respond. Continue</td>
</tr>
<tr>
<td>24</td>
<td>Profits off the scale. Fear crash. :P</td>
</tr>
<tr>
<td>25</td>
<td>Revenue plateau'd out. Selecting one cell to observe change.</td>
</tr>
<tr>
<td>26</td>
<td>Decrease in cell. Reselect and continue.</td>
</tr>
<tr>
<td>27</td>
<td>No change observed.</td>
</tr>
<tr>
<td>28</td>
<td>No reason to change</td>
</tr>
<tr>
<td>29</td>
<td>[NONE]</td>
</tr>
<tr>
<td>30</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>
C.8 Subject 8

Age: 27  
Language: **English**  
StudyLevel: **PhD**  
StudyArea: **Geography**  
StudyYear: **4th**  
Total Earned: **£8.65**

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Trying a variety of field lay outs- sidpersed and blocky to see what works</td>
</tr>
<tr>
<td>2</td>
<td>DARK blue is more profitable?</td>
</tr>
<tr>
<td>3</td>
<td>[NONE]</td>
</tr>
<tr>
<td>4</td>
<td>Profits are now dropping in dark blue areas, and increasing in light blue. Going to switch some dark -¿ lightt</td>
</tr>
<tr>
<td>5</td>
<td>Thats made it worse!</td>
</tr>
<tr>
<td>6</td>
<td>There is going to be a point soon when dark and light switch over, so im going to switch all to light and leave it for a few turns..</td>
</tr>
<tr>
<td>7</td>
<td>[NONE]</td>
</tr>
<tr>
<td>8</td>
<td>[NONE]</td>
</tr>
<tr>
<td>9</td>
<td>[NONE]</td>
</tr>
<tr>
<td>10</td>
<td>[NONE]</td>
</tr>
<tr>
<td>11</td>
<td>[NONE]</td>
</tr>
<tr>
<td>12</td>
<td>[NONE]</td>
</tr>
<tr>
<td>13</td>
<td>[NONE]</td>
</tr>
<tr>
<td>14</td>
<td>[NONE]</td>
</tr>
<tr>
<td>15</td>
<td>[NONE]</td>
</tr>
<tr>
<td>16</td>
<td>[NONE]</td>
</tr>
<tr>
<td>17</td>
<td>[NONE]</td>
</tr>
<tr>
<td>18</td>
<td>[NONE]</td>
</tr>
<tr>
<td>19</td>
<td>I may have made more money by leaving it dark blue...</td>
</tr>
<tr>
<td>20</td>
<td>[NONE]</td>
</tr>
<tr>
<td>21</td>
<td>[NONE]</td>
</tr>
<tr>
<td>22</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>
23 Sudden drop in profits, switching back to dark blue
24 [NONE]
25 [NONE]
26 Do I make more money by accepting the continual losses of the dark blue, or the gradual increase of light blue. Prob better with dark blue as, even if it goes doen, it is still more than light blue very gradually increasing then crashing.
27 [NONE]
28 [NONE]
29 [NONE]
30 [NONE]
31 [NONE]
32 [NONE]
33 [NONE]
34 [NONE]
35 [NONE]
36 [NONE]
37 [NONE]
38 [NONE]
39 [NONE]
40 [NONE]

Table C.15: Recorded narratives from subject 8 - experiment 1

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Going to leave it alone to see what the trends are</td>
</tr>
<tr>
<td>2</td>
<td>[NONE]</td>
</tr>
<tr>
<td>3</td>
<td>[NONE]</td>
</tr>
<tr>
<td>4</td>
<td>CHanging some over to see what happens as the profits are flat atm swapping them round. LT and BTR better with dark blue</td>
</tr>
<tr>
<td>5</td>
<td>[NONE]</td>
</tr>
<tr>
<td>6</td>
<td>[NONE]</td>
</tr>
<tr>
<td>7</td>
<td>[NONE]</td>
</tr>
<tr>
<td>8</td>
<td>[NONE]</td>
</tr>
<tr>
<td>9</td>
<td>[NONE]</td>
</tr>
<tr>
<td>10</td>
<td>[NONE]</td>
</tr>
<tr>
<td>11</td>
<td>[NONE]</td>
</tr>
<tr>
<td>12</td>
<td>Profits dropping, switching LU</td>
</tr>
<tr>
<td>13</td>
<td>[NONE]</td>
</tr>
<tr>
<td>14</td>
<td>[NONE]</td>
</tr>
<tr>
<td>15</td>
<td>[NONE]</td>
</tr>
<tr>
<td>16</td>
<td>Getting worried that Im missing changes by monoculture.</td>
</tr>
<tr>
<td>17</td>
<td>[NONE]</td>
</tr>
<tr>
<td>18</td>
<td>Getting worried that Im missing changes by monoculture.</td>
</tr>
</tbody>
</table>
Prices are flat. Don’t know what to do as everything I change makes it worse.

Light green very good but is it the area or the colour?

Oh hang on it's the colour

switching everything to light green

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I have selected random cells along the edge of the grid, as this is my starting go. No strategy other than edge cells</td>
</tr>
<tr>
<td>2</td>
<td>All the initially selected edge cells have shown stronger than average improvement, so I am going to select the rest of the edge cells and a few random central ones</td>
</tr>
<tr>
<td>3</td>
<td>All non-selected cells have performed poorer than average, so I am going to select all the central cells and unselect some of the top and bottom edge cells</td>
</tr>
<tr>
<td>4</td>
<td>I’m going to see how this strategy evolves for a couple of rounds</td>
</tr>
<tr>
<td>5</td>
<td>[NONE]</td>
</tr>
<tr>
<td>6</td>
<td>I’ve selected all the cells now except the central one, as I am now searching for a strategy to increase my decidedly average performance!</td>
</tr>
<tr>
<td>7</td>
<td>[NONE]</td>
</tr>
<tr>
<td>8</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>
9 I have selected more central cells to try to change performance, as I don't appear to be gaining anything now
10 I am deselecting all the cells to see what happens
11 None selected was bad, except for a central part. I am now going to try a cross-shape with the central 5 cells not selected
12 [NONE]
13 I'm expanding the cross to a central square, as it seems leaving the external cells unchanged doesn't improve them continuously
14 The last round proved good for all the cells in the square central area, so now I am trying an alternative selection of edges cells
15 Now I am trying just four selected cells on the compass points of the edge, as I am still looking for a strategy to maximise all the cells in the editor
16 That last round improved some of the edge cells. I am going to experiment with selecting the corners only
17 I am going to change this slightly by selecting the central cell
18 It appears as if edge cells don't really like to be kept as the same selection for more than one round, and therefore have to be continuously changed and rechanged? I am going to take this stragey on for the next few rounds. The central cells seem to like being unselected, though none of my cells is doing above average!
19 [NONE]
20 [NONE]
21 [NONE]
22 Having none selected has doing pretty well for the last couple of rounds. I'll try altering some a random selection of about 4 cells throughout the grid to see what happens
23 Oh that a was terrible last round. Have I damaged something?!
24 It looks like something has changed drastically. I am going to try remedial action, whereby I'll try my cross-type selection for the central cells only and see what happens
25 [NONE]
26 [NONE]
27 I'm going to expand a cross to a square in the centre
28 [NONE]
29 [NONE]
30 I'm going to add into the selection some external blocks to see can than increase the revenue
31 Finally add in all the blocks bar the centre - perhaps this will help increase revenue, by altering the land use
32 [NONE]
33 I'm deselecting the 9 central cells now, as the very centre cell (c3) has been doing very well
34 [NONE]
35 I am slowly deselecting some of the edge cells too to see if that increases revenue.
Appendix C. Abstract Land Use Experiment: Subject Narratives

Table C.17: Recorded narratives from subject 9 - experiment 1

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Selecting just the central cell, as it is my first round. This is to see what happens</td>
</tr>
<tr>
<td>2</td>
<td>Deselected the central cell (c3) and selected (a1), again just to see what happens.</td>
</tr>
<tr>
<td>3</td>
<td>Cell A1 did really well, so I am going to expand the area around it to include B1 and A2</td>
</tr>
<tr>
<td>4</td>
<td>Expanding the area about A1, B1 and A2 by three more cells more plus adding in cell E5</td>
</tr>
<tr>
<td>5</td>
<td>Only the corner cells appear to respond best, so I am selecting the corner cells and alternate edge cells to see what happens now.</td>
</tr>
<tr>
<td>6</td>
<td>A5 and E1 did badly, so I have deselected them. I am trying a diagonal line across the grid from cell A1 to E5</td>
</tr>
<tr>
<td>7</td>
<td>I’m not very sure what strategy here is producing revenue, so I am going to assume that the top left and bottom right corners are good. I’ve selected 4 cell square areas about these points to see what happens now</td>
</tr>
<tr>
<td>8</td>
<td>I am going to try a central cross figure, which is unselected to see what happens now. Using two 4 cell squares in the last round wasn’t particularly good or bad.</td>
</tr>
<tr>
<td>9</td>
<td>From the previous round the top right and bottom corners just don’t respond well to being selected. I’m trying to see what happens if I select cells c2 and c4 and leave out a1 and e5</td>
</tr>
<tr>
<td>10</td>
<td>That strategy didn’t improve much either. I’m delecting all cells to see what happens.</td>
</tr>
<tr>
<td>11</td>
<td>I am selecting all cells to see what happens</td>
</tr>
<tr>
<td>12</td>
<td>It appears that really only the top left and bottom right 4-cell corners are responding to changes at the moment</td>
</tr>
<tr>
<td>13</td>
<td>Aha! Something has now changed. I am going to select all the cells again to see if they now respond to being selected</td>
</tr>
<tr>
<td>14</td>
<td>[NONE]</td>
</tr>
<tr>
<td>15</td>
<td>Selecting all cells improved the revenue slightly but I am now going to see if I can find a pattern that produces an improvement on that revenue</td>
</tr>
<tr>
<td>16</td>
<td>[NONE]</td>
</tr>
<tr>
<td>17</td>
<td>[NONE]</td>
</tr>
<tr>
<td>18</td>
<td>[NONE]</td>
</tr>
<tr>
<td>19</td>
<td>I can’t seem to improve the cells by changing them. I am going to try some further random pattern changes.</td>
</tr>
<tr>
<td>20</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>
Table C.18: Recorded narratives from subject 9 - experiment 2

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>21</td>
<td>[NONE]</td>
</tr>
<tr>
<td>22</td>
<td>[NONE]</td>
</tr>
<tr>
<td>23</td>
<td>[NONE]</td>
</tr>
<tr>
<td>24</td>
<td>[NONE]</td>
</tr>
<tr>
<td>25</td>
<td>[NONE]</td>
</tr>
<tr>
<td>26</td>
<td>Hmm, leaving the cells alone for a few rounds has improved them. I’ll change a couple of more cells and see if they can improve too</td>
</tr>
<tr>
<td>27</td>
<td>[NONE]</td>
</tr>
<tr>
<td>28</td>
<td>[NONE]</td>
</tr>
<tr>
<td>29</td>
<td>I’ll add in another couple of cells 3 and a3 to see what happens, as these are adjacent to the 4-cell squares</td>
</tr>
<tr>
<td>30</td>
<td>[NONE]</td>
</tr>
</tbody>
</table>
Appendix D

Abstract Land Use Experiment: Java Agent Model of Subject 7

addMotive(new Motive(this, 1, null){
    private boolean[] conds;
    public int service(){
        if(conds == null) isViable();
        dropMotive(14); // This and motive 14 are mutually exclusive
        if(conds[0]) say("Develop all squares evenly");
        else if(conds[1]) say("Select whole field");
        else if(conds[2]) say("Re-select all");
        else{ System.out.print("ERROR! m1: Condition match failed!"); return FAILURE; }

        LandUseScheme s = (LandUseScheme)getBelief(LAND_USE);
        int rows = (Integer)getBelief(NUMROWS);
        int cols = (Integer)getBelief(NUMCOLS);
        for(int i = 0; i < rows; i++) for(int j = 0; j < cols; j++)
            s.setLandUse(i, j, USE_SELECTED);

        return SUCCESS;
    }
    public boolean isViable(){
        conds = new boolean[]{
            parent.id == ROOT_MOTIVE,
            parent.id == 3,
            parent.id == 2,
            parent.id == 14,
        }
        if(conds[0]) say("Develop all squares evenly");
        else if(conds[1]) say("Select whole field");
        else if(conds[2]) say("Re-select all");
        else{ System.out.print("ERROR! m1: Condition match failed!"); return FAILURE; }

        LandUseScheme s = (LandUseScheme)getBelief(LAND_USE);
        int rows = (Integer)getBelief(NUMROWS);
        int cols = (Integer)getBelief(NUMCOLS);
        for(int i = 0; i < rows; i++) for(int j = 0; j < cols; j++)
            s.setLandUse(i, j, USE_SELECTED);

        return SUCCESS;
    }
}
addMotive(new Motive(this, 2, null) {
    private boolean[] conds;
    public int service() {
        if (conds == null) isViable();

        if (conds[0]) say("leave all unselected.");
        else if (conds[1]) {
            raiseAndExec(newMotive(1, this));
        }
        else if (conds[2]) say("All squares responded uniformly to the selection, all positive. Continue this process.");
        else if (conds[3]) {
            dropMotive(3);
            say("Increase seen once again in selected area. Area that has been constantly selected still shows a decline however is still green so will continue with the whole of the field selected.");
        }
        else if (conds[4]) {
            say("Dramatic decrease in areas not selected. Continue with the selection of all areas");
            raiseAndExec(newMotive(7, this));
            say("as production still green");
        }
        else if (conds[5]) say("Increase still visible. As previous.");
        else if (conds[6]) say("All areas respond to this. Same strategy for this round.");
        else if (conds[7]) {
            dropMotive(5);
            say("Increase seen. Centre areas which were not selected still increasing. Decide to stick with selection pattern for another round.");
        }
        else if (conds[8]) say("Increase observed. Continue the strategy");
        else if (conds[9]) {
            dropMotive(12);
        }
    }
});
say("Selected areas show overall improvement. Keep selected area the same.");
raiseAndExec(newMotive(13, this));
}
else{ System.out.print("ERROR! m2: Condition match failed!");
return FAILURE; }

return SUCCESS;
}
public boolean isViable(){
int rows = (Integer)getBelief(NUMROWS);
int cols = (Integer)getBelief(NUMCOLS);
int n = rows * cols;
conds = new boolean[]{
parent.id == 9,
parent.id == 8 && agent.inContext(1) &&
(Integer)getBelief(ALL_RV_NDC) == n,
agent.inContext(1) && (Double)getBelief(ALL_RV_UN) <= UNIFORM &&
(Integer)getBelief(ALL_RV_NGR) == n,
agent.inContext(3) && (Double)getBelief(SWP2_RV_CH) > DELTA &&
(Double)getBelief(SLP_RV_CH) < -DELTA &&
(Double)getBelief(SLP_RV_OV) >= GREEN,
agent.inContext(1) && agent.inContext(7) &&
(Double)getBelief(SWP_RV_CH) < -DRAMATIC_DECREASE &&
(Double)getBelief(SL_RV_OV) >= GREEN,
agent.inContext(2) && agent.inContext(14) &&
(Integer)getBelief(ALL_RV_NGR) == n,
agent.inContext(14) && (Integer)getBelief(ALL_RV_NGR) == n,
agent.inContext(5) && (Double)getBelief(SWP2_RV_CH) > DELTA &&
(Double)getBelief(DSLP_RV_CH) > DELTA,
agent.inContext(14) && (Integer)getBelief(EXP_MTN_CH) > 0,
agent.inContext(12) && (Double)getBelief(SWP2_RV_CH) > IMPROVEMENT,
};
for(boolean t : conds) if(t) return true; return false;
}

addMotive(new Motive(this, 3, null){
private boolean[] conds;
public int service(){

Appendix D. Abstract Land Use Experiment: Java Agent Model of Subject 7

if(conds == null) isViable();

if(conds[0]){
    dropMotive(14);
dropMotive(8);
say("Centre cell shows increase however all have plummeted.");
raiseAndExec(newMotive(5, this));
say("to try and remediate");
}
else if(conds[1]){
    dropMotive(8);
dropMotive(4);
say("Sudden drop in half of field that is not selected. Decrease still evident in selected half.");
raiseAndExec(newMotive(1, this));
say("to try to reverse the decline.");
}
else if(conds[2]){
    dropMotive(2);
dropMotive(14);
say("All areas crash!");
raiseAndExec(newMotive(1, this));
say("to try and remediate.");
raiseAndExec(newMotive(8, this));
}
else{ System.out.print("ERROR! m3: Condition match failed!");
    return FAILURE; }

return SUCCESS;
}

public boolean isViable(){
    int nc = (Integer)getBelief(NUMROWS) * (Integer)getBelief(NUMCOLS);
    conds = new boolean[]{
        agent.inContext(8) && agent.inContext(14) &&
            (Integer)getBelief(ALL_RV_NPL) >= nc - 1 &&
            (Double)getBelief(DSLP_RV_CH) > DELTA,
        agent.inContext(8) && agent.inContext(4) &&
            (Double)getBelief(SWP_RV_CH) < -DROP &&
            (Double)getBelief(SL_RV_CH) < -DELTA,
        agent.inContext(14) && (Integer)getBelief(ALL_RV_NPL) == nc,
    };
    for(boolean t : conds) if(t) return true; return false;
addMotive(new Motive(this, 4, null){
    public int service(){
        say("Select only half the field");

        LandUseScheme s = (LandUseScheme)getBelief(LAND_USE);
        int rows = (Integer) getBelief(NUMROWS);
        int cols = (Integer) getBelief(NUMCOLS);
        for(int i = 0; i < rows; i++) for(int j = 0; j < cols; j++)
            s.setLandUse(i, j, j <= cols / 2 ? USE_SELECTED : USE_DESELECTED);
        dropMotive(1);

        return SUCCESS;
    }
    public boolean isVisible(){
        return parent.id == 8; // Only ever raised by m8
    }
});

addMotive(new Motive(this, 5, null){
    public int service(){
        say("select worse affected areas");
        say("around outside");
        LinkedList<LandCell> wCells = (LinkedList<LandCell>)getBelief(SWP_CH_WST);
        LandUseScheme s = (LandUseScheme)getBelief(LAND_USE);
        for(LandCell c : wCells){
            s.setLandUse(c.x, c.y, USE_SELECTED);
        }
        return SUCCESS;
    }
    public boolean isVisible(){
        return parent.id == 3; // Only activated by m3
    }
});
addMotive(new Motive(this, 6, null){
    public int service(){
        say("leave centre unselected (it was the most green)");
        LandUseScheme s = (LandUseScheme)getBelief(LAND_USE);
        LinkedList<LandCell> mg = (LinkedList<LandCell>)getBelief(DSL_RV_MAX);
        for(LandCell lc : mg){
            s.setLandUse(lc.x, lc.y, USE_DESELECTED);
        }
        return SUCCESS;
    }
    public boolean isViable(){
        return parent.id == 8; // Only activated by m8
    }
});

addMotive(new Motive(this, 7, null){
    private boolean[] conds;
    public int service(){
        if(conds == null) isViable();
        int n = 1;
        boolean toAdd = false;

        if(conds[0]){  
            say("Further test cells opened up");
            n = 4; toAdd = false;
        } else if(conds[1]){  
            say("(-2 cells)");
            n = 2; toAdd = false;
        } else if(conds[2]){  
            say("Deselecting more cells");
            n = 2; toAdd = true;
        } else{ System.out.print("ERROR! m7: Condition match failed!");
            return FAILURE; }

        LandUseScheme s = (LandUseScheme)getBelief(LAND_USE);
LinkedList<LandCell> tCells = (LinkedList<LandCell>)getBelief(TEST_CELLS);
// If not adding to existing cells,
// then remove and switch back previous test cells
if(!toAdd){
    for(LandCell tc : tCells) s.setLandUse(tc.x, tc.y, USE_SELECTED);
    tCells.clear();
}
// Generate a list of cells as test cell candidates
LinkedList<LandCell> candCells = new LinkedList<LandCell>();
int rows = (Integer)getBelief(NUMROWS);
int cols = (Integer)getBelief(NUMCOLS);
for(int i = 0; i < rows; i++) for(int j = 0; j < cols; j++)
    if(s.getLandUse(i, j) == USE_SELECTED) candCells.add(new LandCell(i, j));
if(candCells.size() == 0) return FAILURE;
// Randomly select cells from the candidate list
// and add to existing test cells
while(n-- > 0 && candCells.size() > 0){
    LandCell nCell = candCells.remove(nextRand(candCells.size()));
    // Set land use for test cell
    tCells.add(nCell);
}
// Set deselected use for all test cells
for(LandCell tc : tCells){
    s.setLandUse(tc.x, tc.y, USE_DESELECTED);
}
return SUCCESS;
}
public boolean isViable(){
    conds = new boolean[]{
        parent.id == 8,
        parent.id == 2,
        parent.id == 9,
    };
    for(boolean t : conds) if(t) return true; return false;
}
});

addMotive(new Motive(this, 8, null){
private boolean[] conds;
public int service(){
    if(conds == null) isViable();

    if(conds[0]){
        raiseAndExec(newMotive(6, this));
        say("to observe changes.");
    }
    else if(conds[1]){
        dropMotive(3);
        dropMotive(1);
        dropMotive(6);
        say("Green areas restored. Centre cell shows increase also.");
        raiseAndExec(newMotive(14, this));
        say("to see if previous patterns of before (1 round decline then steady increase are shown.");
    }
    else if(conds[2]){
        dropMotive(1);
        say("Decrease continues.");
        raiseAndExec(newMotive(4, this));
        say("to investigate consequence.");
    }
    else if(conds[3] && nextRand(2) <= 0){
        say("All Squares show a decrease.");
        raiseAndExec(newMotive(2, this));
        say("to investigate whether this is a blip or not.");
    }
    else if(conds[4]){
        dropMotive(2);
        say("Decline still evident.");
        raiseAndExec(newMotive(7, this));
        say("to monitor the effects of not selected areas.");
    }
    else if(conds[5]){
        raiseAndExec(newMotive(7, this));
        say("to monitor the effects of not selected areas.");
    }
    else{ System.out.print("ERROR! m8: Condition match failed!");
        return FAILURE; }
    return SUCCESS; 
}
public boolean isViable(){
    int all = (Integer)getBelief(NUMCOLS) * (Integer)getBelief(NUMROWS);
    conds = new boolean[]{
        parent.id == 3,
        agent.inContext(1) && agent.inContext(3) &&
        (Double)getBelief(SL_RV_OV) >= GREEN &&
        (Double)getBelief(DSL_RV_CH) > DELTA,
        agent.inContext(1) && agent.inContext(2) &&
        agent.inContext(8) &&
        (Integer)getBelief(ALL_RV_NDC) == all,
        agent.inContext(1) && agent.inContext(2) &&
        (Integer)getBelief(ALL_RV_NDC) == all,
        agent.inContext(1) && agent.inContext(2) &&
        (Integer)getBelief(ALL_RV_NDC) == all,
        agent.inContext(1) && (Double)getBelief(SL_RV_CH) < DELTA &&
        (Double)getBelief(SL_RV_CH) > -DELTA,
    };
    for(boolean t : conds) if(t) return true; return false;
}

addMotive(new Motive(this, 9, null){
    private boolean[] conds;
    public int service(){
        if(conds == null) isViable();
        if(conds[0]){
            dropMotive(14);
            raiseAndExec(newMotive(11, this));
            say("to stimulate growth.");
        }
        else if(conds[1]){
            say("Cells not selected respond and show increase.");
            raiseAndExec(newMotive(7, this));
            say("to try and stimulate increase.
            Selected cells still showing minimal decrease.");
        }
        else if(conds[2]){
            say("expected decrease observed.");
            raiseAndExec(newMotive(2, this));
        }
    }
});
say("hope for increase!");
}
else if(conds[3]){ // Added to balance model
    raiseAndExec(newMotive(14, this));
say("to stimulate growth.");
}
else if(conds[4]){ // Added to balance model
    raiseAndExec(newMotive(14, this));
say("to stimulate growth.");
}
else{ System.out.print("ERROR! m9: Condition match failed!");
    return FAILURE; }

return SUCCESS;
}
public boolean isViable(){
    conds = new boolean[]{
        parent.id == 10,
        agent.inContext(7) && !agent.inContext(9) &&
        (Double)getBelief(DSL_RV_CH) > DELTA &&
        (Double)getBelief(SL_RV_CH) < -DELTA,
        agent.inContext(14) &&
        (Double)agent.getBelief(EXP_SWP_CH) < 0 &&
        (Double)agent.getBelief(DSL_RV_CH) > PLUMMET,
        agent.inContext(4) && (Double)getBelief(SWP_RV_CH) > DELTA,
        agent.inContext(7) && (Double)getBelief(SWP_RV_CH) > INCREASE,
    };
    for(boolean t : conds) if(t) return true; return false;
}
});

addMotive(new Motive(this, 10, null){
    int delay;
    public int service(){
        if(delay == 1) say("Minimal increase shown in previously selected cells.
        Decrease continues in selected cells. Decide to let
        decrease continue until roughly half of scale then
deselect and reselect to stimulate growth.");
        if(delay-- > 0) return RUNNING;
        dropMotive(7);
public void init(){
    delay = 1;
}

public boolean isViable(){
    return agent.inContext(9) && agent.inContext(7) &&
    !agent.inContext(10) && (Double)getBelief(SWP_RV_CH) < DELTA &&
    (Double)getBelief(SL_RV_CH) < -DELTA;
}

addMotive(new Motive(this, 11, null){
    boolean deselected;
    public int service(){
        LandUseScheme s = (LandUseScheme)getBelief(LAND_USE);
        int rows = (Integer)getBelief(NUMROWS);
        int cols = (Integer)getBelief(NUMCOLS);
        if(!deselected){
            say("deselect and reselect");
            for(int i = 0; i < rows; i++) for(int j = 0; j < cols; j++)
                s.setLandUse(i, j, (s.getLandUse(i, j) + 1) % 2);
            deselected = true;
            return RUNNING;
        }
        say("Deselect selected areas. Select those not previously selected.");
        for(int i = 0; i < rows; i++) for(int j = 0; j < cols; j++)
            s.setLandUse(i, j, (s.getLandUse(i, j) + 1) % 2);
        return SUCCESS;
    }
    public void init(){
        deselected = false;
    }
    public boolean isViable(){
        return parent.id == 9; // Only activated by m9
    }
});
addMotive(new Motive(this, 12, null){
    private boolean[] conds;
    public int service(){
        if(conds == null) isViable();

        if(conds[0]){  
            dropMotive(10); //System.out.println("DROPPED M 10!");
            dropMotive(11);
            dropMotive(9);
            say("Growth seen to be stimulated in some areas, less uniform than before. Selecting the areas that did not show any improvement");
        } else{ System.out.print("ERROR! m12: Condition match failed!");
            return FAILURE; }

            LandUseScheme s = (LandUseScheme)getBelief(LAND_USE);
            LinkedList<LandCell> ng = (LinkedList<LandCell>)getBelief(NG_AREAS_D);
            for(LandCell lc : ng) s.setLandUse(lc.y, lc.x, USE_SELECTED);

            return SUCCESS;
        }
        public boolean isViable(){
            conds = new boolean[]{
                agent.inContext(9) && agent.inContext(11) && !agent.isActive(11) && (Integer)getBelief(ALL_RV_NGR) > 0 &&
                (Double)getBelief(ALL_RV_UN) > NOT_UNIFORM,
            };
            for(boolean t : conds) if(t) return true; return false;
    }
});

addMotive(new Motive(this, 13, null){
    public int service(){
        say("Deselect any area that showed a drop");
        LandUseScheme s = (LandUseScheme)getBelief(LAND_USE);
        LinkedList<LandCell> a = (LinkedList<LandCell>)getBelief(SL_AREA_DRP);
        for(LandCell lc : a){
            s.setLandUse(lc.x, lc.y, USE_DESELECTED);
        }
    }
}
return SUCCESS;
}

public boolean isViable(){
    return parent.id == 2; // Only activated by m2
}
}

addMotive(new Motive(this, 14, null){
    private boolean[] conds;
    public int service(){
        if(conds == null) isViable();

        dropMotive(1); // This and motive 1 are mutually exclusive
        if(conds[0])
            System.out.println("continuing with deselect all");
        else if(conds[1]){
            say("Deselect all areas");
        }
        else if(conds[2]){
            say("Deselect all areas");
        }
        else if(conds[3]){
            dropMotive(17);
            say("Decline shown in areas that have been selected. Begin to
                suspect that the system needs to 'recover' after period of use.
                Deselect all areas.");
        }
        else if(conds[4]){
            dropMotive(2);
            dropMotive(13);
            say("Selected areas showing a decline. Feel that they might be over
                exhausted so have deselected most of the grid. Areas of the
                grid still showing increase.");
            raiseAndExec(newMotive(17, this));
        }
        else if(conds[5]){
            say("Selected areas show decrease. Unselected areas show increase.
                Deselect all.");
        }
        else{ System.out.print("ERROR! m14: Condition match failed!");
    }
}
return FAILURE; }

LandUseScheme s = (LandUseScheme) getBelief(LAND_USE);
int rows = (Integer) getBelief(NUMROWS);
int cols = (Integer) getBelief(NUMCOLS);
for(int i = 0; i < rows; i++) for(int j = 0; j < cols; j++)
s.setLandUse(i, j, USE_DESELECTED);

// Motive involves once-only action, always return success
return SUCCESS;
}

public boolean isViable(){
conds = new boolean[]{
    parent.id == 2,
    parent.id == 8,
    parent.id == 9,
    agent.inContext(17) && (Double) getBelief(SL_RV_CH) < -DELTA &&
    (Double) getBelief(SL_EXH) > EXHAUSTED,
    agent.inContext(2) && agent.inContext(13) &&
    (Double) getBelief(SL_RV_CH) < -DELTA &&
    (Double) getBelief(SL_EXH) > EXHAUSTED,
    agent.inContext(2) && agent.inContext(3) &&
    (Double) getBelief(SL_RV_CH) < -DELTA &&
    (Double) getBelief(DSL_RV_CH) > DELTA,
};
if(agent.inContext(14) || agent.inContext(10)) return false;
for(boolean t : conds) if(t) return true; return false;
}

addMotive(new Motive(this, 17, null){
    public int service(){
        say("Select areas that are not showing such strong increase.");
        LandUseScheme s = (LandUseScheme) getBelief(LAND_USE);
        for(LandCell lc : (LinkedList<LandCell>) getBelief(NG_AREAS_D)){
            s.setLandUse(lc.x, lc.y, USE_SELECTED);
        }
        return SUCCESS;
    }
});
Appendix D. Abstract Land Use Experiment: Java Agent Model of Subject 7

```java
public boolean isViable()
{
    return parent.id == 14; // Only activated by 14
}
}
```
Appendix E

Abstract Land Use Experiment: Java Agent Model of Subject 4

```java
addMotive(new Motive(this, 1, null){
    private boolean[] conds;
    public int service(){
        if(conds == null) isViable();
        if(conds[0]) say("Top left dark square (3x3) to start with all the same landuses grouped together");
        else{ System.out.print("ERROR! m1: Condition match failed!");
            return FAILURE; }
        LandUseScheme s = (LandUseScheme)getBelief(LAND_USE);
        Area a = new Area(USE_DARK, s);
        for(int i = 0; i < 3; i++) for(int j = 0; j < 3; j++)
            a.addCell(i, j);
        addBelief(AREA, a);
        return SUCCESS;
    }
    public boolean isViable(){
        conds = new boolean[]{
            parent.id == ROOT_MOTIVE,
        };
        for(boolean t : conds) if(t) return true; return false;
    }
});
```
addMotive(new Motive(this, 2, null){
    private boolean[] conds;
    private String[] phrase = {
        "leaving the same for this round",
        "leaving the same landuse as the last round",
        "leaving same landuse as last round",
        "leaving areas as the same",
        "leaving land use the same",
        "leaving the same landuse",
        "leaving them the same as",
        "leaving squares as they are as",
        "going to leave land use the same this round because",
        "so will leave it",
        "so leaving landuse the same",
        "... going to leave it the same this round",
        "so are going to leave landuse the same",
    };
    private int ph1 = 6; // Index of first 'prefix' phrase
    private int ph2 = 9; // Index of first 'postfix' phrase
    public int service(){
        if(conds == null) isViable();
        String reason = null;
        if(conds[0]){
            
        } else if(conds[1]){
            dropMotive(1);
            reason = "all seem to have started off making ok money";
        } else if(conds[3])
            reason = "that last idea didnt work";
        else if(conds[2])
            reason = "test area losing some money - but still making ok money";
        else if(conds[4])
            reason = "they seem to be ok at the moment";
        else if(conds[5])
            reason = "all areas back to making money";
        else if(conds[6])
            reason = "all areas are making money";
        if(reason == null)
            say(phrase[(int)(rand.nextDouble() * ph1)]);
        else{
            
        }
    }
int ph = ph1 + (int)(rand.nextDouble() * (phrase.length - ph1));
if(ph < ph2)
    say(phrase[ph] + " * " + reason);
else
    say(reason + " * " + phrase[ph]);
}
return SUCCESS;
}
public boolean isViable(){
    conds = new boolean[]{
        parent.id == 8,
        agent.inContext(1) && !agent.inContext(2) &&
        getBelief(AREA) != null &&
        (Double)getBelief(AREA_PROFIT) >= OK_MONEY,
        agent.inContext(2) && getBelief(AREA) != null &&
        (Double)getBelief(AREACHANGE) <= LOSING_SOME &&
        (Double)getBelief(AREA_PROFIT) > OK_MONEY,
        agent.inContext(5) && (Boolean)getBelief(IDEA_WORKED) == false,
        (Double)getBelief(AVG_PROFIT) >= OK_MONEY,
        (Double)getBelief(MIN_PROFIT) >= MAKING_MONEY &&
        (Double)getBelief(AVG_CHANGE) >= BACKTO_MM,
        (Double)getBelief(MIN_PROFIT) >= MAKING_MONEY,
        isActive(PROB_2_7),
    };
    for(boolean t : conds) if(t) return true;
    return false;
}
}
)

addMotive(new Motive(this, 3, null){
    private boolean[] conds;
    private LandUseScheme scheme;
    public int service(){
        if(conds == null) isViable();
        if(conds[0]){
            Area a = (Area)getBelief(AREA);
            String changed = a.remRandom(0.34);
            say("Going to change some of the landuse
                 for the test area (" + changed + ")");
        }
        return SUCCESS;
    }
});
public boolean isViable()
    conds = new boolean[]{
        parent.id == 8,
    };
    for(boolean t : conds) if(t) return true; return false;
}
public void init()
    scheme = (LandUseScheme)getBelief(LAND_USE);
});

addMotive(new Motive(this, 4, null){
    private boolean[] conds;
    private LandUseScheme scheme;
    public int service(){
        if(conds == null) isViable();
        int na = 0; for(boolean i : conds) if(i) na++;
        if(conds[1] || (conds[8] && na == 1)){
            LinkedList<LandCell> u = (LinkedList<LandCell>)getBelief(LOSING_CELLS);
            String changed = "";
            int tochange = conds[1] ? 2 : 3;
            int chFrom = USE_LIGHT;
            for(int i = 0; i < tochange && u.size() > 0; i++){
                LandCell lc = u.remove((int)(rand.nextDouble() * u.size()));
                chFrom = scheme.getLandUse(lc.y, lc.x);
                scheme.setLandUse(lc.y, lc.x, 1 - chFrom);
                if(changed == """) changed += cellStr(lc);
                else changed += ", " + cellStr(lc);
            }
            if(conds[1]){  
                if(rand.nextDouble() < 0.5)
                    say("changing land use of " + changed);
                else
                    say("changing " + changed + " land use to " + USES[1 - chFrom]);
            } else
                say("losing money on area of " + USES[chFrom] + " - so going to try changing " + changed + " to landuse " + USES[1-chFrom]);
        } else if(conds[6] && (na == 1 || (na == 2 && conds[8]))){
            LinkedList<LandCell> v = (LinkedList<LandCell>)getBelief(WORST_LOSING);
String changed = "";
int i = 0;
for(LandCell lc : v){
    scheme.setLandUse(lc.y, lc.x, 1 - scheme.getLandUse(lc.y, lc.x));
    if(changed == "") changed += cellStr(lc);
    else changed += "", " + cellStr(lc);
}
say("changing landuse of all the areas doing the worst in terms of
   money and are also losing money - so changing " + changed);
}
else{
    LinkedList<LandCell> w = (LinkedList<LandCell>)getBelief(WORST_CELLS);
    String changed = "";
    int i = 0;
    for(LandCell lc : w){
        if(i == 3 && conds[3]) break;
        if(i == 2 && conds[4]) break;
        scheme.setLandUse(lc.y, lc.x, 1 - scheme.getLandUse(lc.y, lc.x));
        if(changed == "") changed += cellStr(lc);
        else changed += "", " + cellStr(lc);
        i++;
    }
    if(conds[0])
        say("going to try and change landuse of " + changed);
    else if(conds[2])
        say("changing landuse of " + changed);
    else if(conds[3])
        say("Going to change the landuse of " + changed +
           " as making the least money");
    else if(conds[4])
        say("change landuse on squares " + changed + " they are
           a couple of the squares earning the least amount of money");
    else if(conds[5])
        say("Changing squares " + changed +
           " as earning least amount of money");
    else if(conds[7])
        say("all landuse went really bad so changing " + changed +
           " as the whole area went to losing money and
           they are the worst performing areas");
}
return SUCCESS;
public boolean isViable(){
    conds = new boolean[]{
        parent.id == 6,
        parent.id == 8 && parent.condTrue(3),
        parent.id == 8 && parent.condTrue(4),
        agent.inContext(2) && isActive(PROB_4_3),
        agent.inContext(2) && isActive(PROB_4_4),
        agent.inContext(4) && isActive(PROB_4_5),
        ((LinkedList)getBelief(WORST_LOSING)).size() > 0,
        (Double)getBelief(MAX_PROFIT) <= REALLY_BAD &&
        (Double)getBelief(AVG_CHANGE) < WENT_BAD,
        ((LinkedList<LandCell>)getBelief(LOSING_CELLS)).size() > 0,
    };
    for(boolean t : conds) if(t) return true; return false;
}

public void init(){
    scheme = (LandUseScheme)getBelief(LAND_USE);
}

addMotive(new Motive(this, 5, null){
    private boolean[] conds;
    private LandUseScheme scheme;
    public int service(){
        if(conds == null) isViable();
        int chFrom = USE_LIGHT;
        String changed = "";
        if(conds[0]){
            LinkedList<LandCell> b = (LinkedList<LandCell>)getBelief(BEST_NBRS);
            if(b.size() == 0){
                System.out.println("ERROR! m4: No cells with profitable neighbours.");
                return FAILURE;
            }
            for(LandCell lc : b){
                chFrom = scheme.getLandUse(lc.y, lc.x);
                scheme.setLandUse(lc.y, lc.x, 1 - chFrom);
                if(changed == "") changed += cellStr(lc);
                else changed += ", " + cellStr(lc);
            }
            if(rand.nextDouble() < 0.25)
                say("change squares " + changed + " to see if it is affected"};
        }
    }
}
Appendix E. Abstract Land Use Experiment: Java Agent Model of Subject 4

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by landuse of higher revenue close by");
else if(rand.nextDouble() < 0.33)
say("going to change land use of " + changed +
" as close to other areas doing well");
else if(rand.nextDouble() < 0.5)
say("changing ares " + changed + " to "

+USES[1-chFrom] +

" as areas close by are doing ok");
else
say("going to change " + changed + " to land use " + USES[1-chFrom] +
" so see if close association to areas doing better helps");
}
else if(conds[1]){
LinkedList<LandCell> q = (LinkedList<LandCell>)getBelief(LOSING_NBRSB);
if(q.size() == 0){
System.out.println("ERROR! m4: No falling
cells with profitable neighbours.");
return FAILURE;
}
for(LandCell lc : q){
chFrom = scheme.getLandUse(lc.y,lc.x);
scheme.setLandUse(lc.y, lc.x, 1 - chFrom);
if(changed == "") changed += cellStr(lc);
else changed += ", " + cellStr(lc);
}
if(rand.nextDouble() < 0.5)
say("changed the landuse of the areas " + changed +
" as these ares are losing money and
are close to areas doing better");
else
say("losing money on all the " + USES[chFrom] +
" areas so changing " + changed + " to "

+ USES[1-chFrom] +

" as areas close by are doing better");
}
return SUCCESS;
}
public boolean isViable(){
conds = new boolean[]{
((LinkedList<LandCell>)getBelief(BEST_NBRS)).size() > 0 &&
isActive(PROB_5_0),
((LinkedList<LandCell>)getBelief(LOSING_NBRSB)).size() >= 4,
};
for(boolean t : conds) if(t) return true; return false;


public void init()
{
    scheme = (LandUseScheme)getBelief(LAND_USE);
}
});

addMotive(new Motive(this, 6, null){
    private boolean[] conds;
    private LandUseScheme scheme;
    public int service(){
        if(conds == null) isViable();
        int chTo = USE_LIGHT;
        if(conds[0] || conds[1]){
            String changed = "";
            for(LandCell lc : (LinkedList<LandCell>)getBelief(CHANGED_CELLS)){
                chTo = 1 - scheme.getLandUse(lc.y,lc.x);
                scheme.setLandUse(lc.y, lc.x, chTo);
                if(changed == "") changed += cellStr(lc);
                else changed +=", " + cellStr(lc);
            }
            if(conds[0])
                say("changing " + changed + " back as they
                    are not making much money at all");
            else if(conds[1])
                if(rand.nextDouble() < 0.5)
                    say("this didnt work so will change those areas back");
                else
                    say("that didnt really work - so are going to change them back");
        }
        else if(conds[2]){
            String changed = "";
            for(LandCell lc : (LinkedList<LandCell>)getBelief(CHANGED_WORSE)){
                chTo = 1 - scheme.getLandUse(lc.y,lc.x);
                scheme.setLandUse(lc.y, lc.x, chTo);
                if(changed == "") changed += cellStr(lc);
                else changed +=", " + cellStr(lc);
            }
            String kept = "";
            for(LandCell lc : (LinkedList<LandCell>)getBelief(CHANGED_BETTER)){
                // code to do nothing
if(kept == "") kept += cellStr(lc);
else kept += ", " + cellStr(lc);
}
say(kept + " improved on the last round. So only going to change " +
changed + " back to " + USES[chTo]);
}
return SUCCESS;
}

public boolean isViable(){
conds = new boolean[]{
    agent.inContext(4) && (Double)getBelief(CHN_PROFIT) <= NOT_MUCH_AT_ALL,
    (agent.inContext(4) || agent.inContext(5)) &&
    (Boolean)getBelief(IDEA_WORKED) == false,
    ((LinkedList)getBelief(CHANGED_BETTER)).size() > 0 &&
    ((LinkedList)getBelief(CHANGED_WORSE)).size() > 0,
    for(boolean t : conds) if(t) return true; return false;
}

public void init(){
scheme = (LandUseScheme)getBelief(LAND_USE);
}

addMotive(new Motive(this, 8, null){
    private boolean[] conds;
    public int service(){
        if(conds == null) isViable();
        if(conds[0]){
            dropMotive(4);
            raiseAndExec(newMotive(2, this));
            say(" want to see what happens");
            say(" and even though the top left box is losing money
                - its only a little bit");
        }
        if(conds[1]){
            raiseAndExec(newMotive(3, this));
            say(" just to see what happens and if this increases revenue");
        }
        if(conds[2]){
            raiseAndExec(newMotive(2, this));
            say(" to observe what happens");
        }
if(conds[3]) {
    raiseAndExec(newMotive(4, this));
    if(rand.nextDouble() < 0.5)
        say(" to see if can increase profit on these areas");
    else
        say(" to see if it improves profit");
}
if(conds[4]) {
    raiseAndExec(newMotive(4, this));
    say(" to see if it will increase profits");
}
return SUCCESS;

public boolean isViable() {
    conds = new boolean[] {
        agent.inContext(4) && getBelief(AREA) != null &&
            (Double) getBelief(AREA_CHANGE) < LOSING_A_LITTLE,
        agent.inContext(2) && agent.inContext(8) && isActive(PROB_8_1),
        agent.inContext(5) && isActive(PROB_8_2),
        ((LinkedList<LandCell>) getBelief(LOSING_CELLS)).size() > 0 &&
            isActive(PROB_8_3),
        ((LinkedList<LandCell>) getBelief(WORST_CELLS)).size() > 0 &&
            isActive(PROB_8_4),
    };
    for(boolean t : conds) if(t) return true; return false;
}
public boolean condTrue(int c) { return conds[c]; }
}
Appendix F

Data for Simulation Runs on Agent 4

Figure F.1: Recorded vs simulated use count, Subject 4, Game 2, Run #0

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>A0, A1, B0, B1 improved on the last round. So only going to change A2, B2, C0, C1, C2 back to light</td>
</tr>
<tr>
<td>3</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>4</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>5</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>6</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>7</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>8</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>9</td>
<td>going to change A2, B2, C0, C1, C2 to land use dark so see if close association to areas doing better helps</td>
</tr>
<tr>
<td>10</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>11</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
</tbody>
</table>
they seem to be ok at the moment so will leave it
Going to change the landuse of A3, A4, B3 as making the least money
leaving them the same as they seem to be ok at the moment
leaving them the same as they seem to be ok at the moment
they seem to be ok at the moment so leaving landuse the same
going to leave land use the same this round because they seem to be ok at the moment
they seem to be ok at the moment ... going to leave it the same this round
leaving them the same as they seem to be ok at the moment
going to change land use of D0, D1, D2, D3 as close to other areas doing well
going to change A4 to land use light so see if close association to areas doing better helps
leaving squares as they are as they seem to be ok at the moment
changed the landuse of the areas A3, B2, B3, C2, D0, D1, D2, D3 as these ares are losing money and are close to areas doing better
changed the landuse of the areas A1, A2, B1, C0, C1 as these ares are losing money and are close to areas doing better
going to leave land use the same this round because they seem to be ok at the moment
they seem to be ok at the moment so leaving landuse the same
going to leave it the same this round
they seem to be ok at the moment so will leave it
Going to change the landuse of B0 as making the least money
they seem to be ok at the moment so are going to leave landuse the same

Table F.1: Simulated narratives for Subject 4, Game 2, Run #0
Appendix F. Data for Simulation Runs on Agent 4

Figure F.2: Recorded vs simulated use count, Subject 4, Game 2, Run #1

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>A0, A1, B0, B1 improved on the last round. So only going to change A2, B2, C0, C1, C2 back to light</td>
</tr>
<tr>
<td>3</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>4</td>
<td>change landuse on squares A2, A3 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>5</td>
<td>going to change land use of A3 as close to other areas doing well</td>
</tr>
<tr>
<td>6</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>7</td>
<td>going to change land use of A2 as close to other areas doing well</td>
</tr>
<tr>
<td>8</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>9</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>10</td>
<td>going to change land use of A2, B2, C0, C1, C2 as close to other areas doing well</td>
</tr>
<tr>
<td>11</td>
<td>change landuse on squares A3, A4 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>12</td>
<td>change landuse on squares B3, B4 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>13</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>14</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>15</td>
<td>change landuse on squares C3, C4 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>16</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>17</td>
<td>going to change D0, D1, D2, D3, D4 to land use dark so see if close association to areas doing better helps</td>
</tr>
<tr>
<td>18</td>
<td>changing ares E4 to dark as areas close by are doing ok</td>
</tr>
<tr>
<td>19</td>
<td>changing ares E3 to dark as areas close by are doing ok</td>
</tr>
<tr>
<td>20</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>21</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>22</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td></td>
<td>Event Description</td>
</tr>
<tr>
<td>---</td>
<td>-------------------</td>
</tr>
<tr>
<td>23</td>
<td>changing areas D0, D1 to light as areas close by are doing ok</td>
</tr>
<tr>
<td>24</td>
<td>changed the landuse of the areas C0, C1, C2, D2, D3, E3 as these areas are losing money and are close to areas doing better</td>
</tr>
<tr>
<td>25</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>26</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>27</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>28</td>
<td>changing areas B3 to light as areas close by are doing ok</td>
</tr>
<tr>
<td>29</td>
<td>losing money on all the dark areas so changing A2, A3, A4, B0, B1, B2, B4, C3, C4, D4, E4 to light as areas close by are doing better</td>
</tr>
<tr>
<td>30</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
</tbody>
</table>

Table F.2: Simulated narratives for Subject 4, Game 2, Run #1
### Step Narrative

1. Top left dark square (3x3) to start with all the same landuses grouped together
2. change squares A2, B2, C0, C1, C2 to see if it is affected by landuse of higher revenue close by
3. leaving them the same as they seem to be ok at the moment
4. leaving them the same as they seem to be ok at the moment
5. leaving them the same as they seem to be ok at the moment
6. going to leave land use the same this round because they seem to be ok at the moment
7. leaving them the same as they seem to be ok at the moment
8. they seem to be ok at the moment ... going to leave it the same this round
9. going to leave land use the same this round because they seem to be ok at the moment
10. changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A2, A3, A4, B2, B3, B4, C0, C1, C2, C3, C4, D0, D1, D2, D3, D4, E0, E1, E2, E3, E4
11. changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A4, E0
12. going to change A4, E0 to land use dark so see if close association to areas doing better helps
13. change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money
14. they seem to be ok at the moment ... going to leave it the same this round
15. Going to change the landuse of A4, E0 as making the least money
16. they seem to be ok at the moment ... going to leave it the same this round
17. going to leave land use the same this round because they seem to be ok at the moment
18. they seem to be ok at the moment ... going to leave it the same this round
19. change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money
20. they seem to be ok at the moment so leaving landuse the same
21. changing landuse of A3, B3, B4, D0, D1, E1 to see if it will increase profits
22. losing money on all the dark areas so changing A2, B2, C0, C1, C2, C3, C4, D2, E2 to light as areas close by are doing better

### Figure F.3: Recorded vs simulated use count, Subject 4, Game 2, Run #2

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>change squares A2, B2, C0, C1, C2 to see if it is affected by landuse of higher revenue close by</td>
</tr>
<tr>
<td>3</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>4</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>5</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>6</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>7</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>8</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>9</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>10</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A2, A3, A4, B2, B3, B4, C0, C1, C2, C3, C4, D0, D1, D2, D3, D4, E0, E1, E2, E3, E4</td>
</tr>
<tr>
<td>11</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A4, E0</td>
</tr>
<tr>
<td>12</td>
<td>going to change A4, E0 to land use dark so see if close association to areas doing better helps</td>
</tr>
<tr>
<td>13</td>
<td>change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>14</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>15</td>
<td>Going to change the landuse of A4, E0 as making the least money</td>
</tr>
<tr>
<td>16</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>17</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>18</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>19</td>
<td>change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>20</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>21</td>
<td>changing landuse of A3, B3, B4, D0, D1, E1 to see if it will increase profits</td>
</tr>
<tr>
<td>22</td>
<td>losing money on all the dark areas so changing A2, B2, C0, C1, C2, C3, C4, D2, E2 to light as areas close by are doing better</td>
</tr>
</tbody>
</table>
losing money on all the dark areas so changing A1, B0, B1, D3, D4, E3 to light as areas close by are doing better

leaving them the same as they seem to be ok at the moment

they seem to be ok at the moment ... going to leave it the same this round

they seem to be ok at the moment so leaving landuse the same

going to leave landuse the same this round because they seem to be ok at the moment

they seem to be ok at the moment so leaving landuse the same

Going to change the landuse of A0, E4 as making the least money

leaving them the same as they seem to be ok at the moment

Table F.3: Simulated narratives for Subject 4, Game 2, Run #2
Figure F.4: Recorded vs simulated use count, Subject 4, Game 2, Run #3

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A2, B2, C0, C1, C2</td>
</tr>
<tr>
<td>3</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>4</td>
<td>they seem to be ok at the moment so are going to leave landuse the same</td>
</tr>
<tr>
<td>5</td>
<td>going to change A2, B2, C0, C1, C2 to land use dark so see if close association to areas doing better helps</td>
</tr>
<tr>
<td>6</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>7</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>8</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>9</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>10</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>11</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A3, A4, B3, B4, C3, C4, D0, D1, D2, D3, D4, E0, E1, E2, E3, E4</td>
</tr>
<tr>
<td>12</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A4, E0</td>
</tr>
<tr>
<td>13</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A4, E0</td>
</tr>
<tr>
<td>14</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>15</td>
<td>Going to change the landuse of A4, E0 as making the least money</td>
</tr>
<tr>
<td>16</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>17</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>18</td>
<td>Going to change the landuse of A4, E0 as making the least money</td>
</tr>
<tr>
<td>19</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>20</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>21</td>
<td>they seem to be ok at the moment so are going to leave landuse the same</td>
</tr>
<tr>
<td>22</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>23</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>24</td>
<td>change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>25</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>26</td>
<td>changed the landuse of the areas A3, B3, B4, D0, D1, E1 as these areas are losing money and are close to areas doing better</td>
</tr>
<tr>
<td>27</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>28</td>
<td>they seem to be ok at the moment so are going to leave landuse the same</td>
</tr>
<tr>
<td>29</td>
<td>losing money on all the dark areas so changing A2, B2, C0, C1, C2, C3, C4, D2, E2 to light as areas close by are doing better</td>
</tr>
<tr>
<td>30</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
</tbody>
</table>

Table F.4: Simulated narratives for Subject 4, Game 2, Run #3
Step | Narrative
---|---
1 | Top left dark square (3x3) to start with all the same landuses grouped together
2 | leaving squares as they are as all seem to have started off making ok money
3 | Going to change the landuse of A2, B2, C0 as making the least money
4 | change landuse on squares C1, C2 they are a couple of the squares earning the least amount of money
5 | leaving squares as they are as they seem to be ok at the moment
6 | change landuse on squares A2, A3 they are a couple of the squares earning the least amount of money
7 | going to leave land use the same this round because they seem to be ok at the moment
8 | they seem to be ok at the moment ... going to leave it the same this round
9 | going to leave land use the same this round because they seem to be ok at the moment
10 | they seem to be ok at the moment so leaving landuse the same
11 | Going to change the landuse of A4, B2, B3 as making the least money
12 | B2, B3 improved on the last round. So only going to change A4 back to light
13 | leaving squares as they are as they seem to be ok at the moment
14 | they seem to be ok at the moment so will leave it
15 | leaving squares as they are as they seem to be ok at the moment
16 | they seem to be ok at the moment ... going to leave it the same this round
17 | change squares C0 to see if it is affected by landuse of higher revenue close by
18 | they seem to be ok at the moment so will leave it
19 | change landuse on squares A4, B4 they are a couple of the squares earning the least amount of money
20 | they seem to be ok at the moment so leaving landuse the same
21 | change landuse on squares A4 they are a couple of the squares earning the least amount of money
22 | Going to change the landuse of A3, B3, B4 as making the least money
23 | leaving them the same as they seem to be ok at the moment
24 | they seem to be ok at the moment so leaving landuse the same
25 | changing areas A2, B2, C0 to light as areas close by are doing ok
Going to change the landuse of A1, B0, B1 as making the least money
change squares A0 to see if it is affected by landuse of higher revenue close by
they seem to be ok at the moment so are going to leave landuse the same
leaving them the same as they seem to be ok at the moment
change landuse on squares A0, A1 they are a couple of the squares earning the least amount of money

**Table F.5: Simulated narratives for Subject 4, Game 2, Run #4**
Appendix F. Data for Simulation Runs on Agent 4

Figure F.6: Recorded vs simulated use count, Subject 4, Game 2, Run #5

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>A0, A1, B0, B1 improved on the last round. So only going to change A2, B2, C0, C1, C2 back to light</td>
</tr>
<tr>
<td>3</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>4</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>5</td>
<td>Going to change the landuse of A2, A3, A4 as making the least money</td>
</tr>
<tr>
<td>6</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>7</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>8</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>9</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>10</td>
<td>change squares A4 to see if it is affected by landuse of higher revenue close by</td>
</tr>
<tr>
<td>11</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing B2, B3, B4, C0, C1, C2, C3, C4, D0, D1, D2, D3, D4, E0, E1, E2, E3, E4</td>
</tr>
<tr>
<td>12</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A4</td>
</tr>
<tr>
<td>13</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>14</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>15</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>16</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>17</td>
<td>Going to change the landuse of A4, E0 as making the least money</td>
</tr>
<tr>
<td>18</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>19</td>
<td>going to change land use of A4, E0 as close to other areas doing well</td>
</tr>
<tr>
<td>20</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>21</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>22</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>23</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>24</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>25</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td></td>
<td>Simulated narratives for Subject 4, Game 2, Run #5</td>
</tr>
<tr>
<td>---</td>
<td>-------------------------------------------------</td>
</tr>
<tr>
<td>26</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>27</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>28</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>29</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>30</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
</tbody>
</table>
### Step Narrative

1. Top left dark square (3x3) to start with all the same landuses grouped together
2. Changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A2, B2, C0, C1, C2
3. Leaving them the same as they seem to be ok at the moment
4. Changing landuse on squares A2, A3 they are a couple of the squares earning the least amount of money
5. They seem to be ok at the moment so are going to leave landuse the same
6. Going to change the landuse of A3 as making the least money
7. They seem to be ok at the moment so are going to leave landuse the same
8. Going to change the landuse of A2 as making the least money
9. Changing landuse of A2, A3, A4, B2, B3, B4, C0, C1, C2, C3, C4, D0, D1, D2, D3, D4, E0, E1, E2, E3, E4 to see if it will increase profits
10. D3, D4, E3, E4 improved on the last round. So only going to change A2, A3, A4, B2, B3, B4, C0, C1, C2, C3, C4, D0, D1, D2, E0, E1, E2 back to light
11. They seem to be ok at the moment ... going to leave it the same this round
12. They seem to be ok at the moment so will leave it
13. Leaving them the same as they seem to be ok at the moment
14. Going to change the landuse of A2, A3, A4 as making the least money
15. Leaving them the same as they seem to be ok at the moment
16. Going to change the landuse of B2, B3, B4 as making the least money
17. Change squares C0, D2, E2 to see if it is affected by landuse of higher revenue close by
18. They seem to be ok at the moment so will leave it
19. They seem to be ok at the moment so will leave it
20. Change squares B3, B4 to see if it is affected by landuse of higher revenue close by
21. They seem to be ok at the moment so will leave it
22. Losing money on all the dark areas so changing A2, A3, A4, B0, B1, B2, C0, D2, D3, D4, E2 to light as areas close by are doing better

---

#### Figure F.7: Recorded vs simulated use count, Subject 4, Game 2, Run #6

![Graph showing recorded vs simulated use count]
Appendix F. Data for Simulation Runs on Agent 4

24 going to change A1, E3 to land use light so see if close association to areas doing better helps
25 change landuse on squares A0, E4 they are a couple of the squares earning the least amount of
26 money
27 changing landuse of A0, A1, A2, A3, A4, B0, B1, B2, B3, B4, C0, C1, C2, C3, C4, D0, D1, D2,
28 D3, D4, E0, E1, E2, E3, E4 to see if it will increase profits
29 changing landuse of all the areas doing the worst in terms of money and are also losing money -
30 so changing A4, E0
31 leaving squares as they are as they seem to be ok at the moment
32 changed the landuse of the areas A3, B3, B4, D0, D1, E1 as these areas are losing money and are
33 close to areas doing better
34 changing areas A2, B2, C0, C1, C2, C3, C4, D2, E2 to light as areas close by are doing ok

Table F.7: Simulated narratives for Subject 4, Game 2, Run #6

<table>
<thead>
<tr>
<th>Time</th>
<th>Real</th>
<th>Simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>30</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure F.8: Recorded vs simulated use count, Subject 4, Game 2, Run #7
<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>going to leave land use the same this round because all seem to have started off making ok money</td>
</tr>
<tr>
<td>3</td>
<td>leaving them the same as test area losing some money - but still making ok money</td>
</tr>
<tr>
<td>4</td>
<td>changing ares A2, B2, C0, C1, C2 to light as areas close by are doing ok</td>
</tr>
<tr>
<td>5</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>6</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>7</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>8</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>9</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>10</td>
<td>changing ares A2, B2, C0, C1, C2 to dark as areas close by are doing ok</td>
</tr>
<tr>
<td>11</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A3, A4, B3, B4, C3, C4, D0, D1, D2, D3, D4, E0, E1, E2, E3, E4</td>
</tr>
<tr>
<td>12</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A4, E0</td>
</tr>
<tr>
<td>13</td>
<td>change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>14</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>15</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>16</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>17</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>18</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>19</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>20</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>21</td>
<td>they seem to be ok at the moment so are going to leave landuse the same</td>
</tr>
<tr>
<td>22</td>
<td>they seem to be ok at the moment so are going to leave landuse the same</td>
</tr>
<tr>
<td>23</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>24</td>
<td>change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>25</td>
<td>losing money on all the dark areas so changing A3, B3, B4, D0, D1, E1 to light as areas close by are doing better</td>
</tr>
<tr>
<td>26</td>
<td>changed the landuse of the areas A2, B2, C0, C1, C2, C3, C4, D2, E2 as these ares are losing money and are close to areas doing better</td>
</tr>
<tr>
<td>27</td>
<td>going to change A1, B0, B1, D3, D4, E3 to land use light so see if close association to areas doing better helps</td>
</tr>
<tr>
<td>28</td>
<td>Going to change the landuse of A0, E4 as making the least money</td>
</tr>
<tr>
<td>29</td>
<td>they seem to be ok at the moment so are going to leave landuse the same</td>
</tr>
<tr>
<td>30</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
</tbody>
</table>

Table F.8: Simulated narratives for Subject 4, Game 2, Run #7
Appendix F. Data for Simulation Runs on Agent 4

Figure F.9: Recorded vs simulated use count, Subject 4, Game 2, Run #8

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A2, B2, C0, C1, C2</td>
</tr>
<tr>
<td>3</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>4</td>
<td>changing landuse of A2, A3, A4, B2, B3, B4, C0, C1, C2, C3, C4, D0, D1, D2, D3, D4, E0, E1, E2, E3, E4 to see if it will increase profits</td>
</tr>
<tr>
<td>5</td>
<td>change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>6</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>7</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>8</td>
<td>going to change land use of A3, B3, B4, D0, D1, E1 as close to other areas doing well</td>
</tr>
<tr>
<td>9</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>10</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>11</td>
<td>going to change A3, B3, B4, D0, D1, E1 to land use dark so see if close association to areas doing better helps</td>
</tr>
<tr>
<td>12</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>13</td>
<td>they seem to be ok at the moment so are going to leave landuse the same</td>
</tr>
<tr>
<td>14</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>15</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>16</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>17</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>18</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>19</td>
<td>they seem to be ok at the moment so are going to leave landuse the same</td>
</tr>
<tr>
<td>20</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>21</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>22</td>
<td>losing money on all the dark areas so changing A3, B3, B4, D0, D1, E1 to light as areas close by are doing better</td>
</tr>
</tbody>
</table>
Appendix F. Data for Simulation Runs on Agent 4

23 losing money on all the dark areas so changing A2, B2, C0, C1, C2, C3, C4, D2, E2 to light as areas close by are doing better
24 losing money on all the dark areas so changing A1, B0, B1, D3, D4, E3 to light as areas close by are doing better
25 leaving them the same as they seem to be ok at the moment
26 changing areas A0, E4 to light as areas close by are doing ok
27 Going to change the landuse of A0, A1, A2 as making the least money
28 leaving them the same as they seem to be ok at the moment
29 they seem to be ok at the moment so will leave it
30 leaving them the same as they seem to be ok at the moment

Table F.9: Simulated narratives for Subject 4, Game 2, Run #8
Appendix F. Data for Simulation Runs on Agent 4

Figure F.10: Recorded vs simulated use count, Subject 4, Game 2, Run #9

<table>
<thead>
<tr>
<th>Step</th>
<th>Narrative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Top left dark square (3x3) to start with all the same landuses grouped together</td>
</tr>
<tr>
<td>2</td>
<td>A0, A1, B0, B1 improved on the last round. So only going to change A2, B2, C0, C1, C2 back to light</td>
</tr>
<tr>
<td>3</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>4</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>5</td>
<td>they seem to be ok at the moment so are going to leave landuse the same</td>
</tr>
<tr>
<td>6</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>7</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>8</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>9</td>
<td>going to change land use of A2, B2, C0, C1, C2 as close to other areas doing well</td>
</tr>
<tr>
<td>10</td>
<td>changing landuse of all the areas doing the worst in terms of money and are also losing money - so changing A2, B2, C0, C1, C2</td>
</tr>
<tr>
<td>11</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>12</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>13</td>
<td>changing landuse of A2, A3, A4, B2, B3, B4, C0, C1, C2, C3, C4, D0, D1, D2, D3, D4, E0, E1, E2, E3, E4 to see if it will increase profits</td>
</tr>
<tr>
<td>14</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>15</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>16</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
<tr>
<td>17</td>
<td>change landuse on squares A4, E0 they are a couple of the squares earning the least amount of money</td>
</tr>
<tr>
<td>18</td>
<td>changing landuse of A4, E0 to see if it will increase profits</td>
</tr>
<tr>
<td>19</td>
<td>going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>20</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>21</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>22</td>
<td>they seem to be ok at the moment so leaving landuse the same</td>
</tr>
<tr>
<td>23</td>
<td>they seem to be ok at the moment ... going to leave it the same this round</td>
</tr>
<tr>
<td>24</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td></td>
<td>Going to leave land use the same this round because they seem to be ok at the moment</td>
</tr>
<tr>
<td>---</td>
<td>-----------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>25</td>
<td>leaving them the same as they seem to be ok at the moment</td>
</tr>
<tr>
<td>26</td>
<td>they seem to be ok at the moment so leaving land use the same</td>
</tr>
<tr>
<td>27</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>28</td>
<td>leaving squares as they are as they seem to be ok at the moment</td>
</tr>
<tr>
<td>29</td>
<td>they seem to be ok at the moment so will leave it</td>
</tr>
</tbody>
</table>

Table F.10: Simulated narratives for Subject 4, Game 2, Run #9
Appendix G

Jabuls Dairy Farm Simulator Tutorial
JABLUS Dairy Farm Simulator

Tutorial

Last updated: 19 Aug 09 - 14:00

1. Introduction
2. A quick look round the farm
3. Creating and managing your herd
4. Producing crops for feeds or sale to market
5. Letting the livestock out to graze
6. Saving and re-loading your work

Introduction

This page is a step-by-step walk through the JABLUS Dairy Farm Simulator, to help familiarise the controls and the general farming procedure.

Throughout, there are links to various sections of the User Manual which describes each of the system’s components in more detail.

Before starting the tutorial, make sure the system has been downloaded onto your machine and that it starts up properly. If in doubt, please get in touch!

A quick look round the farm

Once the system is up and running we’re going to start a new simulation in “Stable” mode. To do this do this use the menu to **click on: Simulation -> New -> Stable**

Eventually a new window, which looks similar to the one before should pop up.

Before pressing any buttons, have a little look around the window to see what you have. Some notable features are:

- The **time progress bar** in the centre-top of the window. It shows that the current date is Sunday the 2\textsuperscript{nd} January 2000 (just after the turn of the millennium). The top left of the time progress bar shows the start year (2000) and the top right shows the end year (2010)

\[
\begin{array}{cc}
\text{2000} & \text{2010} \\
\text{Sun 25 Dec 2005} \\
\end{array}
\]

- To the right of the time progress bar you’ll see the **weather forecast**. Because this is the "stable" scenario, the weather has been kept constant to allow an all-year-round growing season. For a more detailed forecast hover the mouse pointer over one of...
the forecast squares, and a small tool-top will pop up showing the forecasted weather. You should see something like: "Mon forecast: rain 3mm, temp 15°C, sun 15.0MJ/m²"

- Just below the weather forecast diagrams are the market price graphs. They show the past year's weekly market prices so you can keep tabs on when products are changing in price. Since no time has passed nothing is shown in the graphs yet. Hover the mouse over each of the check-boxes to find out which colour corresponds to each product. The current price of tradable products can be found when you use the buy/sell buttons (green/red arrows in the top-right). For example, the current price of Grass Silage is £11.26 per tonne. In the stable scenario market prices are kept constant, so for now you can rely on silage always costing £11.26 for the tonne.

- Below the market graphs, on the bottom of the window are the farm stores. There are four of them:

1. The cow steading, to hold your livestock
2. The silage clamp to store all forms of feed silage
3. The feed barn to keep all other feeds and fertilisers dry
4. The slurry pit to store liquid manure, collected from the cow steading and milking parlour

Each store has a horizontal progress bar to show how full it is. The progress bar is coloured according to how much of the space is taken up by each of the products. For example, the screen shot below shows a cow steading (with a maximum capacity of 100 cows) is about two thirds full.
• Above the farm stores is the farm map. It shows all the fields (currently in green), a river running from north to south and some roads in red. The field map comes from a real dairy farm in Dumfries the Crichton Royal Farm, click here to see it in Google maps. All crop/grazing management can be done by right-clicking over the desired field and using the popup menu which appears.

Now that the main simulation window has been introduced, click on the magnifying glass in the top-left row of buttons. This will bring up the evaluation window. It has four tabs, and will allow you to keep track on the farm's vital statistics as the simulation proceeds. Once you're familiar with the farm's visual outputs you're ready to begin farming...

Creating and managing your herd

The cow steading should currently be empty, so the first thing to do is buy some livestock.

1. Click on the buy button in the toolbar
2. Select "Heifer Calves" from the menu
3. A popup will appear to query the number to buy. Type in 150 and click OK

It will be a while before the calves have grown old enough to produce young. In order to start milk production we'll also buy some heifers which have just produced their first calves and are starting to lactate:
1. Click on the buy button again
2. Select "Calved Heifers" from the menu
3. Type in 50 for the quantity and press OK

Livestock prices don't change in the stable scenario, but they will in all other scenarios. Choosing the right times to buy and sell will result in lower costs and higher revenues.

**Feed Management**

Before we can proceed to the next week, we'll need to ensure the herd have enough food to survive, and hopefully produce milk. Click the toolbar button with a cow's head icon (next to the buy/sell buttons). This will open the Feeding Regime window.

There are two separate feeding regimes. The first is for confined livestock and should provide a complete diet to keep the livestock healthy. The second is for grazing livestock, and is there to supplement their main grass diet while grazing. Since it's winter and the livestock are currently confined it will only be necessary to set the ration for confined livestock (top half of the window):

1. Click on the Concentrates box and enter the number 2
2. Then click on the "Grass Silage" box and enter 20

The result of this is that each cow will be offered 2kg of concentrates and 20kg of grass silage each day.

**Start the simulation running**

Now that there is a cow herd, and a feeding regime has been set up, we can watch what happens as we allow the herd to grow. Before continuing, click the magnifying glass again, and select the Livestock Statistics tab. This will show you what's happening to the livestock as time passes.

Now, to set the simulation into motion, click the Play button (the big green triangle button in the toolbar). This causes a single week to pass on the simulated farm, so if you look at the time progress bar it should now say "Sun 9th Jan 2000".

Normally we would carry out various weekly activities on the farm, but for now we're just going to sit back and watch what happens to the herd, so continue clicking the Play button until the time progress bar reaches the 3rd of December. At this point, you'll notice the cow steading starting to gain more cows in their second lactation. This is because the calved heifers bought at the beginning of the year have calved once again. The Livestock Statistics tab in the evaluation window will show you the number of new calves being produced.

If we continue clicking until the 7th of January, the calves bought at the beginning of the year will now be over 1 year old, so automatically move into the next "Heifers 1+" herd group, as visualised in the Cow Steading store of the main window.
Producing crops for feeds or sale to market

Up until now, all feeds have been bought and imported onto the farm, while the farm’s fields have been left unused. In order to make the farm more profitable, we'll start making some grass silage.

Looking at the farm map, there is a key in the bottom right corner showing the colour code each field is given, depending on the current crop. Dark green represents grass not currently being used as pasture. At the moment all fields should be dark green meaning they are all occupied by grass. It is possible to simply harvest what's there already, but because no effort has gone into growing it, the yield will probably be quite low. So we'll start by fertilising the grass:

1. Right click on any field and select "Apply Fertiliser"
2. Enter 200 in the popup to apply 200kg per hectare to the field, click OK
3. Click on the "Nitrate" tab above the map
4. Click the Play button once

The nitrates tab shows you the amount of Nitrogen available to plants in the top 20cm of soil. When play was clicked, the small amount of rain over the week caused the nitrogen from the fertiliser to seep down into the soil profile. Resulting in the field turning dark brown in the nitrates tab. If enough rain falls to saturate the soil, the nitrates will continue to permeate through the soil, and if not taken up by plants, will eventually be leached out of the soil profile. The Leaching tab on the field map shows how much nitrogen has leached from the soil in the past week.

To see the effect the added fertiliser has on the grass, switch to the "Yield" tab. For any crop, this will show you the expected yield in tonnes per hectare. Now click the play button up to the 11th of March. The expected yield of the fertilised field should be much higher than the surrounding un-fertilised fields. To check the exact expected yield, right click over the field. The popup menu should show something like: "Yield: 7.8t/ha".

Now that the grass has grown we're going to harvest it:

1. Right click over the field to harvest
2. Click on "Harvest Crop"

The Silage Clamp store should now have some grass silage stored from the harvest. Since we only harvested one field, the quantity produced is quite small. Time to up-scale our cropping operation...

Mass Production by Grouping Fields and Scheduled Actions

Right-clicking on each individual field to carry out cropping actions, for each week will quickly become very tedious, so two features have been added to make the process easier: (1) Field Grouping and (2) a Cropping Planner.
Create a field group consisting of about half of the total area by doing the following:

1. Hold down the Shift key
2. Click over each field in turn to highlight it
3. Still holding the Shift key, RIGHT click over the final field to add
4. Select “Add to Group” -> “New Group”

All the fields selected will now belong to “Group 1” and can be managed collectively using the cropping planner. To create a plan for this group of fields:

1. Click on the cropping planner button in the toolbar
2. Right click on the left-most green square under the May heading (first week in May)
3. Select “Harvest Crop” from the popup menu
4. Do the same for the first week of July and September
5. Right click over a week in mid-March
6. Select “Spread Slurry ”
7. In the popup which appears, enter 8
8. Do the same for early April, second week in May, early June, second week of July and early August

After following the instructions above, the crop planner should look something like the screenshot below:

The letter S means Spread Slurry, and H means harvest. Further explanation of the codes can be found here.

When executed, this plan will cause slurry to be applied twice before each silage harvest at a quantity of 10m³/ha. Grass which is harvested is automatically added to the silage store.

Now with the cropping planner window still visible, and the field map view set to "Yield": 
[Click play until the beginning of March next year]. While clicking, have a look at the Yield and Nitrates tabs, as well as the silage and slurry stores to see the effect the cropping plan in action.

**Letting the livestock out to graze**

Feeding the cows with harvested silage all-year round is not necessarily the most efficient way to use the farm’s grass resources.
For the remaining fields, not currently being used for silage, enable grazing by:

1. Hold down the Shift key
2. Click over each field to highlight it
3. Still holding the Shift key, RIGHT click over the final field to set
4. Select “Set Grazing On”

Now, the cows need to be let out for grazing. In order to keep milk production up the cows will be confined during the colder winter months, and allowed out to graze in summer.

1. Open the grazing planner
2. In the "Heifers 1+ yrs" row, right click over the first week in April
3. Select “Set Grazing”.
4. In the same row, right click over the last week in September
5. Select “Set Confined”
6. Do the same for all cow groups

When complete the grazing planner should look like this:

<table>
<thead>
<tr>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
<th>Jul</th>
<th>Aug</th>
<th>Sep</th>
<th>Oct</th>
<th>Nov</th>
<th>Dec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heifers 9-1 yrs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heifers 1+ yrs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cows 1st lac</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cows 2nd lac</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cows 3rd+ lac</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Paying attention to the map "Yield" visualisation, the Slurry Pit and the "Grazing Management" section of the Feeding Regime window:

Click next until the end of the year

**Saving and re-loading your work**

After having set up the farm it can be useful to save it for use in the future. Save the simulation run by:

1. Click on “Simulation” -> "Save As..."
2. In save dialog box enter "simulation.sim.csv" as the file name
3. Click OK

Now save the farming regime by:

1. Click on "Regime" -> "Save As..."
2. In save dialog box enter "regime.rgm.csv" as the file name
3. Click OK
Now close the program completely and re-load the Simulation run by:

1. Click on "Simulation" -> "Open..."
2. Browse to and select the file "simulation.sim.csv"
3. Click OK

The simulation should now be re-played exactly as it happened before. If you want to keep running with your original farming regime, load the saved regime by:

1. Click on "Regime" -> "Open..."
2. Browse to and select the file "regime.rgm.csv"
3. Click OK

The grazing planner, cropping planner and feeding regime should now be set-up as before, allowing the farm to continue running.
Overview

The goal of a JABLUS dairy farmer is to run a successful, productive and environmentally friendly dairy farm. The dairy farming system taken as a whole is a very complex one, so it is difficult to find exact definition of a 'successful' and 'productive' dairy farm. For this reason, some performance measures have been provided in the interface to allow the user to judge how well the farm is operating at any moment. The measures use statistics from the model to evaluate performance in four general areas:

- Cropping
- Livestock
- Environmental
- Financial
More information on how to improve performance in each of the areas is provided in the Hints and Tips section.

JABLUS operates on a weekly time step. However, progression through time is controlled by the user, so there is unlimited time to make decisions. Simulations proceed as follows:

1. User chooses actions for the week
2. User clicks Next >> button
3. System simulates a weeks worth of weather, markets, crop growth and cow life
4. System updates interface to reflect new state
5. ...user chooses new actions, and so on...

The only restriction is that users cannot go backwards in time!

The Main Window

The screenshot above shows the main JABLUS screen. Most items in this screen shows the current state of the farm and its environment. All farm controls are accessed via the
tool buttons - labelled (1) on the screenshot. The list below describes the purpose of each of the labelled components.

1. **Tool Bar** to allow control and more detailed assessment of the farm’s state
2. **Visualisation of the simulation time**.
3. **Summary of farm’s performance**
4. **Weather forecast** for the next week
5. **Tabs to select the map visualisation**
6. **Map of the farm area, allowing control over cropping**
7. **Graphs of the past years market prices** for livestock, feeds and milk.
8. **Shows the state of the farm stores**.

**Time Progress Bar**

The time progress bar (top-centre of the main window) visualises simulation time. It shows the year the simulation started (top left of bar), the year it finishes (top right of bar) and the current simulation time (on bar it self). The progress indicator on the bar shows what percentage of the total simulation time has already passed. The small vertical grey notches on the bar divide it by year.

In the screenshot above it shows that the current simulation date is Sunday the 25th December 2005. The simulation started in January 2000, and ends in January 2010. Looking at the progress bar, the simulation is about 60% complete.

The simulation itself takes place on a weekly time step, which means every time the play button is pressed a week’s worth of farm processes is simulated. For the crop and animal models which operate on a daily time-step, 7-days are simulated in each step.

**Farm Performance**

In order to provide a quick view of the farm’s performance, its vital statistics are aggregated to provide a measure of performance in four areas:

- **Cropping**: Overall production, increase in production, percentage area used for cropping, average yield.
- **Livestock**: Herd size, number of new calves, minimal cow losses, milk productivity.
- **Environmental Friendliness**: Manure overflow, nitrate leaching, livestock lost as waste, self sufficiency.
- **Financial Performance**: Profit, balance, value of assets, growth of assets.

The output is a value ranging from 0% (very poor) to 50% (average) to 100% (excellent). The performance summary displayed on the main window shows the current value of
these measures. For values at 50% (such as Crp in the screenshot above) the performance bar shrinks down to a vertical line in the centre. Values close to 50% will be shaded yellow (see Env as an example). For values less than 50% the bar grows further to the left and deepens in red (see Fnc). For values greater than 50% the bar grows out to the right and becomes greener (see Lvs).

A graph of the past year's history of these performance figures can be viewed in the evaluation summary window.

Weather forecast

For each simulation week, a weather forecast is generated and visualised in the seven forecast boxes in the top-right of the main window.

The weather diagrams are similar to those found in news-based forecasts and show the expected sunshine/cloud cover, precipitation and temperature. If the mouse is hovered over a weather diagram the actual weather figures will be revealed. For example, Hovering over Tuesday in the diagram might popup: "Tue forecast: rain 10mm, temp 7.1°C, sun 14.2MJ/m²" Unlike real forecasts, the predictions made here are perfect. If the forecast says there will be 10mm of rain next Tuesday, then there will be exactly that on the day.

In the simulation the weather's main influence is on the cropping system it affects plant growth and uptake/leaching of soil nutrients. The weather generator parameters for the default scenario have been calibrated against weather data from the 2000s around the central belt of Scotland. For this reason the winter brings cold weather making it difficult to grow crops and the summer brings mixed weather with heavy precipitation at times!

Market Price Graphs

Graphs of past market price data are located in the right-hand side of the main window, just below the weather forecast. They show the weekly changes in market prices over the last year. The system generates these prices using a random function which is calibrated against real market price data over the last 10 to 30 years. It means that although the actual values can't be predicted, the nature of their fluctuations and cycles will be similar what's happened in the past.
Because of space limitations, labels haven't been added to the bars directly. Instead, hover the mouse pointer over the coloured checkboxes and the system will reveal what product the colour represents. Checking or unchecking the check boxes shows or hides the line for that particular commodity. The screenshot above shows that purple represents the change in prices for finished heifers. Because it is unchecked, the purple line is not visible in the graph.

The exact current price of these, and all other tradeable products can be found by using the buy and sell buttons in the Tool Bar.

**Farm Stores**

These are used to temporarily store accumulated materials such as feeds, silage, fertiliser and also the animals themselves. Each farm storage area, along with its contents is visualised at the bottom of the main window.

Each store has a horizontal percentage bar to show how full it is. The bar is broken down to show the amount of space each product is occupying. Below the main percentage bar, a key shows the colour representing each storage item, along with the actual quantity stored. The number in the top right of each storage box shows its maximum capacity.

As an example, the screenshot above shows that the cow steading has a maximum capacity of 100 cows. The percentage bar shows its about 70% full, with young heifers up to 1 year old occupying the most space. The key below the bar shows that there are 22 young heifers in the cow steading.

When a store becomes too full to take the products generated by the farm, the system will discard of the remainder in some way. In the case of livestock, the system will automatically send the oldest members of the herd away to be culled. In the case of the silage clamp, any surplus fodder generated is simply sold on the market. In the case of
the Slurry pit, excess slurry is spread among random fields. It is recommended that this is avoided since it can cause pollution and excess nitrate leaching.

**Farm Field Map**

The farm map visualises the farm's land resource and provides control for cropping and grazing management. By selecting from the tabs above the map it is possible to visualise different aspects of each field, including:

- **Crop** (currently shown) shows the crop currently assigned to the field
- **Yield** shows the number of tonnes (dry mass) that would be produced if the crop were immediately harvested (tDM/ha)
- **Water** shows the percentage of water in the top 20cm of the soil
- **Nitrates** shows the quantity of nitrogen available in the top 20cm of the soil (kgN/ha)
- **Leaching** shows the amount of nitrate leached out of the soil profile in the past week (kgN/ha)

Right clicking over a field shows a small description of the field and provides a menu of actions which can be carried out on the field. If an action is disabled (grayed out) it could be because there isn't enough of what's required in the store, or the current state of the field doesn't allow the action to be carried out.

If the same action needs to be carried out on multiple fields, hold down shift and click on the desired fields in turn. Then (still holding shift) right click, and then select the desired action from the menu. Where regular actions need to be carried out at particular times of the year it is possible to set up a **cropping plan** to automatically carry out the tasks according a schedule. Where a scheduler is being used to automatically manage field management, it is possible to group fields so that they are all managed by a single schedule. To do this highlight the desired fields as described above and select "Add to Group".
The screenshot shows that the field selected has the following properties: Its name (or identifier) is: **F19** The crop growing in it is: **Wheat** The size of the field is: **5.8ha**

When right clicking over a field, its name, crop and size is always displayed. The yield, water content, soil nitrates or nitrates leached may also be shown if the corresponding view is selected from the tabs above the map.

**Tool Bar**

The diagram below shows the buttons used to access the system’s main controls. The purpose of each of the controls is described in more detail below. Click on each of the links below for more information on how to use each of the controls:
JABLUS Controls

1. Buy
2. Sell
3. Feeding Regime
4. Grazing Planner
5. Cropping Planner
6. Evaluation
7. Next Week
8. Next Quarter

Moving Forwards
Once farming decisions have been made it’s time to proceed to the next step. The play button advances the simulation by one week. The fast forward button advances the simulation by a quarter (13 weeks).

NOTE: Be aware that after advancing the simulation forwards it is impossible to go back to the previous week(s).

**Buying from Market**

This button allows feeds, fertiliser and livestock to be bought from the market. When its pressed a Popup menu will appear, showing all products available to buy. If something cannot be bought (for example, if the store is already full) then the item will be disabled (greyed out) on the menu. When an item is selected for purchase, a popup will appear to query the quantity desired. Enter the amount and click on OK to complete the purchase.

The price for feeds and livestock varies as time passes. The current price can be checked on the graphs displayed on the main screen.

Sometimes products will be purchased automatically, for example if there are no feeds left in the store. These events can be checked in the weekly list of market transactions in the Weekly Transactions tab of the evaluation window.

**Selling to Market**

Similar to the buy button, the sell button displays a menu of farm products which can be sold. When there is no more of a product left in the farm’s store it will no longer be possible to sell, and the item will be disabled (greyed out) on the menu.
All milk produced by the farm is sold immediately, and not stored on the farm. Any feed and livestock produced are initially placed in farm storage. If the farm stores are allowed to fill to capacity, the system will automatically sell any new feed or livestock which the farm is unable to store. All sales, whether compulsory or voluntary can be tracked in the Weekly Transactions tab of the evaluation window.

**Feeding Regime**

This window allows the user to control the livestock feeding regime. It's divided into four sections:

- **Confined Livestock**: feed allocated to livestock not grazing
- **Grazing Livestock**: feed allocated to grazing livestock
- **Annual Milk Production**: target and actual milk yield
- **Grazing Management**: controls whether cows are grazing or not

All of the feed quantities are expressed in kilograms of fresh weight (kgFW) per cow per day. For each feed budget, the first column (Offered) allows the user to control the quantity offered to each cow for each day. The second column shows how much of the feed offered was actually consumed, and the third column (Remaining) shows how much was remaining at the end of the day. Any feed remaining at the end of the day is discarded.
Feed Budget Window
The feeding budget is split into two groups. The first group is for confined cows and the second is for grazing cows. When the cows are sent out to graze they are automatically moved onto the second feeding budget entitled "Grazing Livestock". As soon as cows are no longer assigned to grazing they go back onto the original "Confined Livestock" feeding budget. The check boxes at the bottom of the window allow the user to control whether cows in each group are put out to graze.

Because milk production is often governed by quotas, the feed budget window also allows control over the target milk yield. The desired annual target yield is set in the field in the first column (Target). The actual yield produced in the last round is projected to a year and displayed in the second column (Actual). The final column (Surplus) displays the difference between the target yield and actual projected yield. If last week's yield was below target then the projected surplus will be negative.

The "Target Yield" box allows control over how intensively the cows are milked. Raising
this value will mean that the cows need a larger ration to produce the higher quantity of milk required.

**Grazing Planner**

Instead of manually controlling cow grazing on a weekly basis, the grazing planner allows users to set up a schedule. For any week grazing is to commence, right click over the relevant square and select "Set Grazing". The planner will then show a small "+" symbol in the square to indicate that grazing commences on that week. It will also change the colour of the subsequent squares to green to indicate that grazing is activated during these weeks. If grazing needs to be stopped at some point, right click over the relevant week in the planner and select "Set Confined". The planner will show a "-" symbol to indicate that grazing is halted on that week. The subsequent squares will also be shaded grey to show that grazing is disabled.

NOTE: The state in the final week of a plan will always continue into the following year. For example, if grazing is currently taking place in the last week in December, it will also take place in the first week of January in the following year, and continue thereafter unless a "Set Confined" action is placed to stop it.

If a plan needs to be amended to start at a different time, right click over the square market with a "+" symbol and select "Set Earlier" or "Set Later". Similarly, if the plan needs to be changed to stop grazing all together, right click over the "+" icon and select Remove.

Another (quicker) method can be used for moving or deleting the "+" and "-" symbols. Simply left click over the symbol so that it is surrounded by a red square. Now click over the new square for the symbol to move it, or click over the same square again to delete it.

**Planner for Grazing Schedule**

The planner in the screenshot above has been set to allow cows in their first lactation to start grazing in the fourth week of March, and continue all the way to third week in August. Cows in their second lactation are also allowed to graze, but they start a week later and end a week earlier. The vertical yellow line in the plan shows the current simulation time (second week in August).

It is possible to manually override the planned grazing schedule by using the checkboxes in the feeding budget window, but be aware that the schedule will continue to run in the background changing the grazing status according to the plan.
Cropping Planner

The cropping planner works in a similar manner to the grazing planner and allows users to schedule cropping actions such as sewing, fertilising and harvesting. It can be accessed either by using the control button (1 in screenshot below), or by right clicking over a field and selecting "Open Crop Planner" (2 in screenshot). When right clicking over a field only the planners relevant to the selected fields will be shown.

Cropping Planner for a group of fields

Managing Field Groups

It is possible to manage field groups explicitly by right clicking over selected fields and using the "Add to Group" or "Remove from Groups". For example, (4) in the diagram would add all the selected fields to group 3. If a field is removed from its group then it won't be affected by any crop plans and will need to be managed manually.

A field can never be in more than one group. If a field which is already part of a group is added to a new or different group, it will automatically be removed from its original group.

To find out which group a field belongs to, right click and select "Open Crop Planner" (2 in the screenshot). This will open the crop planner, highlighting the field's group in the
planner and on the map.

To find out which fields are within a particular group, click on the crop planner control button (1) and then click over the group title (5). This will cause all fields belonging to the group to be highlighted in the map.

**Cropping Planner Action Codes**

- **P** Plough
- **F** Fertilise (quantity expressed as absolute fertiliser weight in kilograms)
- **S** Sprayed Slurry (quantity expressed as volume in cubic meters)
- **G** Sow Grass
- **W** Sow Wheat
- **M** Sow Maize
- **H** Harvest
- **+** Set grazing on
- **-** Set grazing off

**Evaluation Summary**

The evaluation summary tab of the evaluation window is designed to provide a quick view of how successfully the farm is running. It displays the following:

- **Performance Trend:** Graph showing change in measured over the last year. Measured from 0% (very poor) to 50% (average) to 100% (excellent). These are the same figures as those displayed in the farm performance summary on the main window.

- **Financial summary:** Total costs, revenues and growth over the last year, along with value of assets measured by current market prices. The SFP row stands for “Single Farm Payment” and represents a typical government grant received for a farm of this size (200ha) assuming all terms and conditions are met. A breakdown of livestock and feeds financial figures can be found in the livestock statistics and cropping statistics tabs. In addition, a balance sheet detailing all weekly transactions can be found in the Weekly Transactions tab.

- **Environmental statistics:** Measures all aspects considered to be bad for the environment including: Manure Overflow, Surplus feed, leached nitrates, unsellable cows, imported fertiliser, feeds and animals.
NOTE: All figures displayed in the evaluation panel are 'live' and update themselves as soon as any farming actions are carried out. This allows the results of trades, harvests etc to be immediately visible in the evaluation window.

**Livestock Statistics**

The Livestock Statistics tab shows herd population and financial gains and losses related to livestock management over the past year.
Each of the headings in the annual herd statistics table are explained as follows:

- **Group** is the section of the herd the statistics relate to. The herd is arranged into:
  1. Heifers 0-1 yrs = Heifers from 0 to 12 months old
  2. Heifers 1+ yrs = Heifers from over 12 months old which have not yet calved
  3. Cows 1st lac = Heifers which have produced their first calf(s) and are now lactating for the first time
  4. Cows 2nd lac = Cows which have gone through a second pregnancy and are
in their second lactation period

5. Cows 3rd+ lac = Cows which have gone through three or more pregnancies and are in their third or above lactation

- **Avg Number** is the average number of cows in the group over the last year.
- **Calves Produced** is the total number of calves produced by cows in the group over the last year.
- **Culled** is the total number of animals in the group which have been culled over the last year.
- **Milk Produced** is the total quantity produced by each group over the last year.

The financial livestock statistics are again averaged over the year and are explained as follows:

- **Bought** shows how much money was spent on purchases
- **Sold** shows how much revenue was made from sales
- **Stock** is the value measured by the current market prices and the growth in farm value caused by the product over the last year.
- **Growth** includes money spent, money earned and change in stock value. A negative growth implies either the stock value has declined or money has been spent on the product and it has been consumed or lost.

NOTE: These financial figures are aggregated and displayed in the financial statistics table in the Evaluation Summary tab, under the heading 'Livestock'.

**Cropping Statistics**

The Cropping Statistics tab shows all figures relating to crop production including quantities produced and financial expenses of the cropping operation:
The annual cropping statistics table shows the following:

- **Crop** is the crop the statistics are about. One of Grass silage, wheat silage or maize silage.
- **Area Used** is the average field area assigned to this crop over the year (in Hectares)
- **Avg Yield** is the average yield achieved by harvests of this crop over the year (in Tonnes/Hectare).

### Annual Cropping Statistics

<table>
<thead>
<tr>
<th>Crop</th>
<th>Area Used (ha)</th>
<th>Avg Yield (t/ha)</th>
<th>Produced (t)</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grass Silage</td>
<td>211.8</td>
<td>5.0</td>
<td>1487.3</td>
<td>73.6</td>
</tr>
<tr>
<td>Wheat Silage</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Maize Silage</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Total</td>
<td>211.8</td>
<td>5.0</td>
<td>1487.3</td>
<td>73.6</td>
</tr>
</tbody>
</table>

### Annual imports, exports, stock value and growth

<table>
<thead>
<tr>
<th>Product/Service</th>
<th>Bought</th>
<th>Sold</th>
<th>Stock</th>
<th>Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grass Silage</td>
<td>-£19708</td>
<td>£0</td>
<td>£0</td>
<td>-£19708</td>
</tr>
<tr>
<td>Grass Cultivation</td>
<td>£0</td>
<td>-</td>
<td>-</td>
<td>£0</td>
</tr>
<tr>
<td>Grass Harvesting</td>
<td>-£10660</td>
<td>-</td>
<td>-</td>
<td>-£10660</td>
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<tr>
<td>Wheat Silage</td>
<td>£0</td>
<td>£0</td>
<td>£0</td>
<td>£0</td>
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<tr>
<td>Wheat Cultivation</td>
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</tr>
<tr>
<td>Wheat Harvesting</td>
<td>£0</td>
<td>-</td>
<td>-</td>
<td>£0</td>
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<tr>
<td>Maize Silage</td>
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<td>£0</td>
<td>£0</td>
<td>£0</td>
</tr>
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<tr>
<td>Maize Harvesting</td>
<td>£0</td>
<td>-</td>
<td>-</td>
<td>£0</td>
</tr>
<tr>
<td>Concentrates</td>
<td>-£27163</td>
<td>£0</td>
<td>£0</td>
<td>-£27163</td>
</tr>
<tr>
<td>Hay</td>
<td>£0</td>
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<td>£0</td>
<td>£0</td>
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<tr>
<td>Straw</td>
<td>£0</td>
<td>£0</td>
<td>£0</td>
<td>£0</td>
</tr>
<tr>
<td>Fertiliser</td>
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<td>£0</td>
<td>£0</td>
<td>£0</td>
</tr>
<tr>
<td>Fertilising</td>
<td>£0</td>
<td>-</td>
<td>-</td>
<td>£0</td>
</tr>
<tr>
<td>Slurry Spreading</td>
<td>-£1730</td>
<td>-</td>
<td>-</td>
<td>-£1730</td>
</tr>
<tr>
<td>Ploughing</td>
<td>£0</td>
<td>-</td>
<td>-</td>
<td>£0</td>
</tr>
</tbody>
</table>
• **Produced** is the total quantity of silage produced by this crop over the year (in Tonnes).

• **Change** is the change in total annual production compared with the same time last year (in Tonnes). Negative values here mean that a lower total quantity was produced over the past year than over the year before.

The financial cropping statistics show you:

• **Product/Service** is the crop product itself, or the services or products used in crop production.

• **Bought** is the total amount of money spent on buying the product/service over the last year.

• **Sold** is the total amount of money raised on selling the product over the last year.

• **Stock** is the financial value of the farm’s current stock based on the current week’s market price.

• **Growth** is the growth in farm asset value caused by this product/service. For consumable products/services this will always be negative to indicate that use of the product causes a net loss of purely financial value. For products which have been bought and sold, but not consumed a positive value indicates the product was sold at a higher price than it was bought, resulting in a net increase in the farm’s balance. A negative value would indicate that the product was sold for less than it was bought for, resulting in a loss. For crops which are produced, then any on-farm production results in a positive growth since it increases farm assets in the form of stored feeds. Produced crops which are sold also result in a positive growth, since the stored feed asset has simply been converted into stored financial assets. Any consumption of crops yields a negative growth. A self-sufficient farm will produce the same quantity as is consumed and should result in a growth value close to zero, since growth by production cancels out decline by consumption.

NOTE: These financial figures are aggregated and displayed in the financial statistics table in the Evaluation Summary tab, under the heading 'Cropping'.

**Weekly Transactions**

This is the farm’s weekly balance sheet. It shows each individual financial transaction which took place over the last week. The effect on the farm’s overall financial standing is displayed in a summary at the bottom. It shows the total costs for the week, total money raised by revenue, the difference in costs and revenue over the last week (profit) and the farm’s bank balance at the end of the week.
As trades are made this balance will update in real time so that weekly revenues and expenditures can be monitored closely.

**Loading and Saving of simulation data**

The "Simulation" menu at the top allows the following:

- **New** creates a fresh new simulation based on either a pre-set scenario or a "Generated Scenario". A randomly generated scenario is simply a scenario where all the parameters are chosen randomly, based on an initial random seed. Sticking
to the same seed (for example 42) will ensure the same weather, market patterns etc, happening every time the scenario is re-started.

- **Open** allows a pre-saved simulation to be opened and replayed. Only files which end in ".sim.csv" can be opened in the Simulation menu.
- **Save As** allows a currently running simulation to be saved under a new name. By default all simulations are saved under the name "untitled_\(\_\)\(\_\)sim.csv". When saved simulations are re-opened they will automatically run up to the point where they last left off.
- **Quit** closes the program

The "Regime" menu allows users to save and load the farm management regime. This includes the feeding budget, grazing plan and cropping plan. Saved regimes can then be tested out on different scenarios to compare their effectiveness under different conditions.

The regime menu contains the following options

- **New** to clear the current regime and create a fresh blank one.
- **Open** to open a previously saved regime. Files opened with this dialog should have the extension ".rgm.csv"
- **Save** saves the current regime file to preserve any updates which have been made to the regime.
- **Save As** to allow the regime file to be saved under a new name. By default regimes will be saved under the name "untitled_\(\_\)\(\_\)rgm.csv"

A couple important things to note about saving data:

1. Simulation files DO NOT contain any regime information. This means when an old simulation is loaded from a ".sim.csv" file the simulation will play exactly as it happened before, but the cropping/grazing plans will be empty. Remember to load the regime file you were using with the simulation as well.

2. There is no "Save" menu option for simulation files (.sim.csv) because they are saved automatically as the simulation proceeds. This is not the case for regime files (.rgm.csv). If changes are made to a regime, ensure the "Save" option in the Regime menu is used to save any new changes to the regime.
Appendix I

Dairy Experiments: Original Narrative
Data

I.1 Farmer A

02/01/00
- Milk target 7500 L/H. Start with modest achievable target
- Concentrates up to 5kg - reaction to increased target yield
09/01/00
- Grouped all fields into 9 groups, made blocks that gave a variety of sizes & locations on farm
16/01/00
- Upped concentrate to 6kg as yield -356 from target
23/01/00
- Reduced grass silage by 2kg & added 2kg of maize to improve palatability & hopefully induce small increase in yield
06/02/00
- Spread slurry at 50m3 on whole farm - it is close enough to growing season to get a response from slurry in grass growth and far enough away from grazing season not to cause cows not to want to eat grass because of taste of slurry. Weather is also fairly good this week so a good opportunity to have a clear out of the slurry store.
13/02/00
- Bought 20 calved heifers as farm has space & forage for them & milk price is rising 20/02/00
- Milk yield down so added 2kg of wheat silage into diet 12/03/00
- Added 1kg of concentrates as milk yield struggling and this should see them through until grazing starts.
- Spread slurry on croups 2 & 3 as planning to put into crop soon 26/03/00
- Sowed groups 2 & 3 2(wheat) 3(maize) as weather is good
- Bought 150t fertiliser
- Spread 200kg/ha of fertiliser on rest of farm as good weather and will see growth response at this time of year 02/04/00
- Allow 2 groups of young heifers to graze as weather good. Not enough crass to let milkers out yet 09/04/00
- Sow 300kg/ha of fert on groups 1, 5, 8 for silage making 16/04/00
- Bought 50 calved heifers as about to start grazing season & milk price still good 23/04/00
- Apply 150kg/ha to groups 4, 3, 6 & 9 for grazing 20/09/00
- Harvest silage as hit forward 1/4 button by accident! 27/08/00
- Sow 300kg/ha on silage group for regrowth
- Apply 15kg/Ha of fert on grazing to keep growth going 03/09/00
- Harvest wheat - good weather. crop reaching t/ha dry matter 17/09/00
- Bought 25 heifer calves as felt didn’t have enough young stock coming through. 24/09/00
- Bought 50 calved heifer to bolster number & ensure sheds are full to capacity for winter. 19/11/00
- Harvest Maize - DM not good but getting late in year
14/01/01
- Bought 8 calved heifers to fill shed
04/02/01
- Stopped feeding maize & upped wheat to 6kg to try & improve performance
04/03/01
- Changed crop plan to grow all wheat instead of maize as got poor crop of maize
- Sold 10 cull cows as price good & short of space
11/03/01
- Bought shed space for 50 to allow expansion.
- Bought 55 calved heifers as they have got cheaper (995)
18/03/01
- Bought wheat silage as it was cheap (25)
29/04/01
- Sold 500T of silage @ 34 as got plenty & price good.
- Bought accommodation for 50 head to allow expansion
27/05/01
- Increased clamp size as more cattle to feed
30/09/01
- Sold 67T grass silage as pit full & price good.
06/01/02
- Crop rotation. still only wheat no maize
- Built another 50 spaces awaiting heifer prices dropping.
- Sold 2500t silage as haven’t bought heifers yet & still to dear
08/12/02
- Bought 100 more places & 40 heifer to maximise output? & increase assets while heifers are cheap
12/01/03
- Increased slurry storage
27/07/03
- Sold 5000T of silage as good money & got plenty
28/09/03
- Milk price bad so heifers cheap. Capitalise on this by adding 150 spaces & buying 150 heifers @ 795
08/02/09
- Sold heifer calves & bought calved heifers to capitalise on milk price
I.2  Farmer B

02/01/00
- Group fields to ease management and simplify system. Create 3 central blocks. Set crop planning for year.
- Grp 1: Wheat for forache to cows. Set wheat crop plan for block for year.
- Grp 2: Silage cutting fround for silage feeding during winter period. Set fertiliser slurry et for growth.
- Grp 3: Grazing plan for animals during year. Set fertiliser at limits.
- Purchase 35 heifers to milk.
- Set cow frazing groups for year ahead. Set target yield @ 7800 litres average.

24/09/00
- Buy 20 calved heifers in preparation for increase in milk price during winter and maintain production levels.

08/10/00
- Increase concentrates to 4kg/head to increase milk production

31/12/00
- Up milk yield target to 8500 litres

14/01/01
- Purchase 12 calved heifers due to rising milk price

21/01/07
- Reduce feeding of silage to 22 litres due to high wastage

04/02/01
- Delete slurry application to wheat (grp 1) due to 4t of leaching, also store has
- Increase concentrates 1kg to 5kg to lift milk yield

08/04/01
- Purchase 25 heifer calves for future milking to lift cow herd (is?)

29/04/01
- Remove fertiliser from group 3 grazing block. (250kg delete) as hight nitrates - yield OK

05/08/01
- As above - repeat
19/08/01
- Purchase 500m³ silage clamp for extra storage for grass silage harvest.
02/12/01
- Require to purchase livestock housing 50 head
23/12/01
- Remove slurry application in grp3 as not required
06/01/02
- Purchase 50 head livestock housing as young stock is growing to limit/capacity
19/05/02
- Purchase 20 calved heifers due to rising milk price & good silage stocks
18/08/02
- Sell maize silage to create capacity for store (200t). Sell grass silage (300t) also to create capacity for store.
10/11/02
- Spread slurry group 2 to avoid spillage
22/12/02
- Sell 22 cows 3rd lact to make way for heifers
05/01/03
- Purchase 100 cow steading places to allow for young stock (is?) (eutting?) herd
12/01/03
- Flip rotation grp 3 with grp1
13/07/03
- Build extra silage pit space 5000m³
02/11/03
- Purchase 100m³ slurry pit for all these cows!
04/01/04
- Sell cows 3rd lact+ = 18, grass silage = 1500t, hay = 200t – Surplus stocks
10/10/04
- Purchase 150 steading space for growing (is?) alter slurry application due to filling pit
17/10/04
- Purchase 200m³ slurry for capacity.
02/01/05
- Cropping changes significant.
Appendix I. Dairy Experiments: Original Narrative Data

- Grp 2 only 1 cut silage and increase grazing offer.
  03/04/05
- Reomve april fertilser on wheat
  25/09/05
- Urgently over slurry capacity + 3000m3
  20/11/05
- Cull cows sell 27
- Heifer calves sell 30 ... price good
  09/04/06
- Sell calved heifers x10 .. price good
  10/12/06
- Sell cull cows = 34 .. price good
  17/12/06
- Price good, sell valved heifers = 40
  07/01/07
- Good price for cull cows, sell 33
  22/04/07
- Good price for calved heifers sell 19
  06/05/07
- Good price for calved heifers sell 4
  07/10/07
- Good price for calved heifers sell 19
  23/12/07
- Sell cull cows. good price. sell 22
  19/10/08
- Sell calved heifers. Good price near capacity x20
  09/11/08
- Sell cows in 3rd lactation, good price, near capacity x29
  14/12/08
- Sell cows in 3rd lactation, good price, near capacity x30
  04/01/09
- Reintroduced 2nd silage harvest period in group 2. Areer due to poor weather and poor stocks
  ??/02/09
- Redo diets to address low silage stocks
Appendix I. Dairy Experiments: Original Narrative Data

22/02/09
- Sell cull cows 60 due to good price
22/03/09
- Sell cull cows 50 due to good price

I.3 Farmer C

Initial set up:
Group 1 96.6 ha
Group 2 28.7 ha
Group 3 46.5 ha
Group 4 20.2 ha
Group 5 15.8 ha

01/01/00
- Bought 100 calved heifers and 8 heifer calves to increase output
06/02/00
- Whole farm slurry/30 m3 except group 5 -¿ 45 m3
02/01/00
- Split farm into 5 groups
  1 Silage
  2 Grazing
  3 Cow grazing
  4 Maize
  5 Wheat
- Bought 100 calved heifers to increase output
- 80 heifer calves to boost youngstock numbers and heifer replacement numbers
- Built extra accommodation for 100 cows
06/08/00
- Bought 50 calved heifers
22/08/00
- Keep 1st calves in early
??/01/04
- Built another 200 cow places, bought 200 heifers  
11/01/04  
- Built 300 m3 slurry  
??/03/08  
- Sold 200 heifers aged 0-1yr  
- Bought 200 calved heifers because milk price is sky high
Appendix J

Dairy Experiments: Narrative Interpretations and Agent Schemas

A description of the process used to interpret the narratives and generate the schema is described in chapter 4. The chapter also presents a concise set of rules for formatting these documents.

J.1 Farmer A
Interpretation

02/01/00
- [m1] Milk target[b1] 7500 L/H. [m2] Start with modest achievable target[b2]
- [m3] Concentrates[b3] up to 5kg - (reaction to increased target yield[b1])

09/01/00

16/01/00
- [m3] Upped concentrate[b3] to 6kg as (yield[b8] -356 from target[b1] )

23/01/00
- [m6] Reduced grass silage by 2kg & [m7] added 2kg of maize to (improve palatability & [m8] hopefully induce small increase in yield[b8] )

06/02/00
- [m9] Spread slurry at 50m3 on whole farm - (it is close enough[b9] to growing season[b10] to get a response from slurry in grass growth) and (far enough[b11] away from grazing season[b18] not to cause cows not to want to eat grass because of taste of slurry). (Weather[b12] is also fairly good this week) so a good opportunity to [m10] have a clear out of the slurry store.

13/02/00
- [m11] Bought 20 calved heifers as (farm has space[b13] & forage[b14] for them & milk price[b15] is rising )

20/02/00
- (Milk yield[b8] down) so [m12] added 2kg of wheat silage into diet

12/03/00
- [m3] Added 1kg of concentrates as (milk yield[b8] struggling) and this should ([m13] see them through until grazing starts).
- [m14] Spread slurry on groups 2 & 3 as ([m15] planning to put into crop soon )

26/03/00
- [m16] Sowed groups 2 & 3 2(wheat) 3(maize) as (weather[b12] is good )
- [m17] Bought 150t fertiliser
- [m18] Spread 200kg/ha of fertiliser on rest of farm as (good weather[b12] and will see growth response at this time of year[b16])

02/04/00
- [m19] Allow 2 groups of young heifers to graze as (weather[b12] good). Not (enough grass[b17]) to [m20] let milkers out yet

09/04/00
- [m21] Sow 300kg/ha of fert on groups 1, 5, 8 for ([m22] silage making)

16/4/00
- [m11] Bought 50 calved heifers as (about to start grazing season[b18] & milk price[b15] still good)

23/04/00
- [m23] Apply 150kg/ha to groups 4, 3, 6 & 9 for [m24] grazing

20/09/00
- [m25] Harvest silage as (hit forward 1/4 button by accident!)

27/08/00
- [m26] Sow 300kg/ha on silage group for [m27] regrowth
- [m21] Apply 15kg/Ha of fert on grazing to ([m28] keep growth going)

03/09/00
- [m29] Harvest wheat - (good weather[b12]. crop reaching t/ha dry matter[b19])

17/09/00
- [m30] Bought 25 heifer calves as (felt didn't have enough young stock[b20] coming through.)
24/09/00
19/11/00
- [m33] Harvest Maize - (DM[b24] not good but getting late in year[b25])
14/01/01
- [m11] Bought 8 calved heifers to ([m32] fill shed)
04/02/01
- [m34] Stopped feeding maize & [m12] upped wheat to 6kg to ([m35] try & improve performance[b26])
04/03/01
- [m36] Changed crop plan to grow all wheat instead of maize as (got poor crop[b24] of maize)
- [m37] Sold 10 cull cows as (price[b27] good & short of space[b13])
11/03/01
- [m38] Bought shed space for 50 to ([m39] allow expansion).
- [m11] Bought 55 calved heifers as (they[b28] have got cheaper (£995))
18/03/01
- [m40] Bought wheat silage as (it[b29] was cheap (£25))
29/04/01
- [m41] Sold 500T of silage @ £34 as (got[b30] plenty & price[b22] good.)
- [m38] Bought accommodation for 50 head to ([m39] allow expansion)
27/05/01
- [m42] Increased clamp size as (more cattle[b13] to feed )
30/09/01
- [m41] Sold 67T grass silage as (pit[b31] full & price[b29] good).
06/01/02
- [m43] Crop rotation. [m36] still only wheat no maize
- [m38] Built another 50 spaces (awaiting heifer prices[b28] dropping).
- [m41] Sold 2500t silage as (haven't bought heifers yet & still to dear[b28] )
08/12/02
- [m38] Bought 100 more places & [m11] 40 heifer to ([m44] maximise output[b32] & [m45] increase assets[b21] while heifers are cheap[b28])
12/01/03
- [m46] Increased slurry storage
27/07/03
- [m41] Sold 5000T of silage as (good money[b29] & got[b30] plenty)
28/09/03
- (Milk price[b15] bad so heifers[b28] cheap). Capitalise on this by [m38] adding 150 spaces & [m11] buying 150 heifers @ £795
08/02/09
- [m47] Sold heifer calves & [m11] bought calved heifers to (capitalise on milk price[b15])
Belief Set

b1. Target Yield
b2. Target Yield that is modest and achievable
b3. Offered concentrates
b4. Field outlines (polygons)
b5. Blocks of fields (polygons)
b6. Field sizes (area)
b7. Field locations
b8. Milk yield
b9. Max length of time before growing season in which spread slurry will result in grass growth
b10. Growing season (time of year)
b11. Min length of time before grazing season in which spread slurry will not affect cow grazing.
b12. Weather (generic, good or bad)
b13. Number of animals in cow steading (also free space)
b14. Total quantity of forage stored
b15. Current milk price
b16. Time of year
b17. Quantity of grass in grazing fields
b18. Grazing season
b19. Wheat dry matter in field
b20. Young stock numbers
b21. Number of calved heifers
b22. Grass silage price
b23. Animal steading capacity
b24. Maize dry matter in field
b25. Point in year at which it is too late to harvest crops
b26. Generic farm performance
b27. Cull cow price
b28. Calved heifer price
b29. Grass silage price
b30. Stock of grass silage
b31. Free space in silage pit
b32. Farm output
## Agent Schema

<table>
<thead>
<tr>
<th>Motive</th>
<th>Precondition(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>m1. Milk target $x$</td>
<td>to satisfy $[m2]</td>
</tr>
<tr>
<td>m2. Start with modest, achievable [milk] target</td>
<td>start of simulation</td>
</tr>
<tr>
<td>m3. Add $+x$ of concentrates</td>
<td>(reaction to increased target yield $[b1]</td>
</tr>
<tr>
<td>m4. Group all fields into $x$ groups</td>
<td>start of simulation</td>
</tr>
<tr>
<td>m5. Make blocks that give a variety of sizes &amp; locations on farm</td>
<td>to satisfy $[m4]$</td>
</tr>
<tr>
<td>m6. Reduced grass silage by $x$</td>
<td>to satisfy $[m8]</td>
</tr>
<tr>
<td>m7. Added $x$ of maize</td>
<td>to satisfy $[m8]</td>
</tr>
<tr>
<td>m8. Improve palatability &amp; hopefully induce small increase in yield</td>
<td>none stated</td>
</tr>
<tr>
<td>m9. Spread slurry at $x$ on whole farm, have a clear out of the slurry store</td>
<td>close enough $[b9]$ to growing season $[b10]$ to get a response from slurry in grass growth AND far enough $[b11]$ away from grazing season $[b18]$ not to cause cows not to want to eat grass because of taste of slurry AND weather $[b12]$ is also fairly good this week $</td>
</tr>
<tr>
<td>m11. Buy $x$ calved heifers</td>
<td>(farm has space $[b13]$ AND forage $[b14]$ for them AND milk price $[b15]$ is rising $</td>
</tr>
<tr>
<td>m12. Added $+x$ of wheat silage into diet</td>
<td>(milk yield $[b8]$ down $</td>
</tr>
</tbody>
</table>
m12. Upped wheat to x OR (to satisfy [m35] | x=6)
m13. See them through until grazing starts grazing not started yet
m14. Spread slurry on groups g to satisfy [m15] | g=2,3
m15. Planning to put into crop soon none stated
m16. Sowed groups g weather [b12] is good | g=2(wheat),3(maize)
m17. Bought x fertiliser to satisfy [m18] | x=150
m18. Spread x of fertiliser on rest of farm good weather [b12] AND will see growth response at this time of year [b16] | x = 200
m19. Allow 2 groups of young heifers to graze weather [b12] good
m20. Let milkers out enough grass [b17]
m21. Sow x of fert on groups g OR (to satisfy [m22] | x=300, g=1,2,8) OR (to satisfy [m24] | x=150, g=3,4,6,9)
m22. Silage making none stated
m24. Grazing none stated
m25. Harvest silage assuming silage had fully grown
m26. Sow x on silage group to satisfy [m27] | x=300
m27. Regrowth none stated
m29. Harvest wheat good weather [b12] AND crop reaching t/ha dry matter [b19]
m30. Buy x heifer calves felt didn't have enough young stock [b20] coming through | x=25
m31. Bolster number none stated
m32. Ensure sheds are full to capacity (for winter) OR (none stated)
m33. Harvest maize DM [b24] not good but getting late in year b25
m34. Stopped feeding maize to satisfy [m35]
m35. Try & improve performance none stated
m36. Changed crop plan to grow all wheat instead of maize (got poor crop [b24] of maize) OR (to satisfy [m43])
m36. Still only wheat no maize
m37. Sold x cull cows price [b27] good AND short of space [b13] | x=10
m38. Bought shed space for x OR (to satisfy [m39] | x=50) OR (awaiting heifer prices [b28] dropping | x=50) OR (to satisfy [m44] AND to satisfy [m45] | x=100) OR (to satisfy [m39] | x=50) OR (to satisfy [m44] AND to satisfy [m45] | x=100)
<table>
<thead>
<tr>
<th>m39. Allow expansion</th>
<th>none stated</th>
</tr>
</thead>
<tbody>
<tr>
<td>m40. Bought wheat silage</td>
<td>it [b29] was cheap</td>
</tr>
<tr>
<td>m41. Sold $x$ of silage</td>
<td>got [b30] plenty AND price [b22] good</td>
</tr>
<tr>
<td>m41. Sold $x$ grass silage</td>
<td>pit [b31] full AND price [b29] good</td>
</tr>
<tr>
<td>m41. Sold $x$ silage</td>
<td>haven't bought heifers yet AND still to dear [b28]</td>
</tr>
<tr>
<td></td>
<td>good money [b29] AND got [b30] plenty</td>
</tr>
<tr>
<td>m42. Increased clamp size</td>
<td>more cattle [b13] to feed</td>
</tr>
<tr>
<td>m43. Crop rotation</td>
<td>none stated</td>
</tr>
<tr>
<td>m44. Maximise output</td>
<td>none stated</td>
</tr>
<tr>
<td>m45. Increase [heifer] assets</td>
<td>heifers are cheap [b28]</td>
</tr>
<tr>
<td>m46. Increased slurry storage</td>
<td>none stated</td>
</tr>
<tr>
<td>m47. Sold heifer calves</td>
<td>capitalise on milk price [b15]</td>
</tr>
</tbody>
</table>
Follow-up Questions

Resolving Reasonless Motives

For the following days, state the reason(s) for the motives or actions quoted:
NOTE: For some of the actions the reason may seem totally obvious. Even where this is the case, providing a reason is useful.

23/01/00 Increasing milk yield
12/03/00 Planning to put groups 2 & 3 into crop soon
09/04/00 Making silage
23/04/00 Grazing the cows
27/08/00 Regrowing the silage crop
24/09/00 Increasing the number of livestock
14/01/01 Filling the livestock shed
04/02/01 Trying to improve performance
11/03/01 Allowing expansion of livestock numbers
06/08/02 Rotating crops
08/12/02 Maximising farm output
12/01/03 Increasing slurry storage

Grounding Beliefs and Actions

On several occasions 'good weather' was described as a reason driving some decisions. Describe in more detail good poor weather is, specifically in terms of rainfall, temperature and/or sunshine.

On 08/12/02 the term 'maximise output' is used. Which specific farm outputs were being maximised?

On 04/02/01 the intention was to try and improve farm performance. Which specific aspects of farm performance were intended to improve.

On 09/01/00 describe in more detail how blocks of grouped fields were created specifically, how were the shapes, sizes and locations decided.
J.2 Farmer B
Interpretation

02/01/00
- Grp 3 = [m12] Grazing plan for animals during year. [m13] Set fertiliser at limits.
- [m14] Purchase 35 heifers to milk.
- [m15] Set cow grazing groups for year ahead. [m16] Set target yield @ 7800 litres average.
24/09/00
- [m14] Buy 20 calved heifers in (preparation for increase in milk price [b2] during winter and [m17] maintain production levels).
08/10/00
- [m18] Increase concentrates to 4kg/head to ([m19] increase milk production )
31/12/00
- [m16] Up milk yield target to 8500 litres
14/01/01
- [m14] Purchase 12 calved heifers (due to rising milk price [b2])
21/01/07
- [m20] Reduce feeding of silage to 22 litres due to (high wastage [b3])
04/02/01
- [m21] Delete slurry application to wheat (Grp 1) due to (^3k of leaching [b4], also store [b5] has)
04/03/01
- [m18] Increase concentrates 1kg to 5kg to ([m19] lift milk yield )
08/04/01
- [m22] Purchase 25 heifer calves for ([m23] future milking to [m24] lift cow herd n's )
29/04/01
- [m25] Remove fertiliser from group 3 grazing block. (250kg delete) as (high nitrates [b6] – yield [b7] OK)
05/08/01
- [m25] As above - repeat
19/08/01
- [m27] Purchase 5000m3 silage clamp for [m28] extra storage for (grass silage harvest[b7]).
23/09/01
- [m29] Reset target milk yield @ 8000 litres as (not achieving [b8] 8500 [b19] currently)
02/12/01
- (Require) to [m30] purchase livestock housing 50 head
23/12/01
- [m21] Remove slurry application in Grp 3 as (not required )
06/01/02
- [m31] Flip rotation Grp 1 with Grp 3 to (address leaching [b4])
27/01/02
- [m30] Purchase 50 head livestock housing as (youngstock n's [b9] growing to limit/capacity[b10] )
19/05/02
- [m14] Purchase 20 calved heifers due to (rising milk price [b2] & good silage stocks [b11] )
18/08/02
- [m32] Sell maize silage to (([m28] create capacity for store (200t)). [m33] Sell grass silage (300t) to (([m28] create capacity for store).
10/11/02
- [m34] Spread slurry group 2 to ([m35] avoid spillage)
22/12/02
- [m43] Sell 22 cows 3rd+ lact to ([m36] make way for heifers)
05/01/03
- [m30] Purchase 100 cow steading places to (allow for young stock n's [b9] entering herd)
12/01/03
- [m31] Flip rotation Grp 3 with Grp1
13/07/03
- [m27] Build extra silage pit space 5000m3
02/11/03
- [m37] Purchase 1000m3 slurry pit for (all these cows [b12]!)
04/01/04
- Sell {4326} cows 3rd lact+ = 18, [m33] grass silage = 1500t, [m38] hay = 200t} due to (surplus stocks[b13,b11,b14])
10/10/04
- [m30] Purchase 150 steading space for (growing n's [b12]) [m26] alter slurry application due to (filling pit [b5])
17/10/04
- [m37] Purchase 2000m3 slurry for ([m47] capacity).
02/01/05
- Cropping changes significant. [m39] Grp 2 only 1 cut silage and [m40] increase grazing offer.
03/04/05
- [m25] Remove April fertiliser on wheat
25/09/05
- (Urgently over [b5] slurry capacity [b15]) [m37] + 3000m3
20/11/05
- [m44] Cull cows sell 27, [m41] heifer calves sell 30 - (price [b16, b17] good)
09/04/06
- [m42] Sell calved heifers x10 - (price [b18] good)
10/12/06
- [m44] Sell cull cows = 34 - (price [b16] good)
17/12/06
- (Price [b18] good), [m42] sell calved heifers = 40
07/01/07
- (Good price [b16] for cull cows), [m44] sell = 33
22/04/07
- (Good price [b18] for calved heifers) [m42] sell = 19
06/05/07
- (Good price [b18] for calved heifers) [m42] sell = 4
07/10/07
- (Good price [b18] for calved heifers) [m42] sell = 19
23/12/07
- [m44] Sell cull cows. (good price [b16]). = 22
19/10/08
- [m42] Sell calved heifers. (Good price [b18], near [b12] capacity [b10]) x20
09/11/08
- [m43] Sell cows in 3rd lact+, (good price [b16], near [b12] capacity [b10]) x29
14/12/08
- [m43] Sell cows in 3rd lact+, (good price [b16], near [b12] capacity [b10]) x30
04/01/09
- [m45] Reintroduced 2nd silage harvest period in Grp 2 area due to (poor weather [b1] and poor
- [m46] Redo diets to address (low silage stocks [b11])
22/02/09
- [m44] Sell cull cows 60 due to (good price [b16])
22/03/09
- [m44] Sell cull cows 50 due to (good price [b16])
Belief Set

b1. Weather ('good' or 'bad')
b2. Milk price: current and projected winter price
b3. Wastage of budgeted feed
b4. Nitrate leaching
b5. Quantity of slurry stored in the slurry pit
b6. Soil nitrate quality
b7. Grass yield in pastures
b8. Cow milk yield
b9. Number of young stock
b10. Capacity of livestock steading
b11. Stock of grass silage
b12. Overall number of livestock
b13. Stock of cows in 3rd+ lactation
b14. Stock of hay
b15. Capacity of slurry pit
b16. Price of cull cows (generic)
b17. Price of heifer calves
b18. Price of calved heifers
b19. Target milk yield

Agent Schema

<table>
<thead>
<tr>
<th>Motive</th>
<th>Precondition(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>m1. Group fields</td>
<td>to satisfy [m2] AND to satisfy [m3] AND simulation start</td>
</tr>
<tr>
<td>m2. Ease management</td>
<td>none stated</td>
</tr>
<tr>
<td>m3. Simplify system</td>
<td>none stated</td>
</tr>
<tr>
<td>m4. Create 3 central blocks</td>
<td>to satisfy [m1]</td>
</tr>
<tr>
<td>m5. Set crop planning for year</td>
<td>simulation start</td>
</tr>
<tr>
<td>m6. Wheat for forage to cows</td>
<td>none stated</td>
</tr>
<tr>
<td>m7. Set wheat crop plan for block for year</td>
<td>to satisfy [m6] AND simulation start</td>
</tr>
<tr>
<td>m8. Silage cutting ground</td>
<td>to satisfy [m9]</td>
</tr>
<tr>
<td>m9. Silage feeding during winter period</td>
<td>none stated</td>
</tr>
<tr>
<td>m10. Set fertiliser</td>
<td>to satisfy [m11]</td>
</tr>
<tr>
<td>m11. Growth</td>
<td>to satisfy [m9]</td>
</tr>
<tr>
<td>m12. Grazing plan for animals during year</td>
<td>none stated</td>
</tr>
<tr>
<td>m13. Set fertiliser at limits</td>
<td>to satisfy [m12]</td>
</tr>
<tr>
<td>m14. Purchase x heifers to milk</td>
<td>(none stated</td>
</tr>
<tr>
<td>m14. Buy x calved heifers</td>
<td>OR</td>
</tr>
<tr>
<td>m14. Purchase x calved heifers</td>
<td>(preparation for increase in milk price [b2] during winter AND to satisfy [m17]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
<th>Conditions</th>
</tr>
</thead>
</table>
| m15 | Set cow grazing groups for year ahead                                        | OR (due to rising milk price [b2] | x=12)
<p>|    |                                                                              | OR (rising milk price [b2] AND good silage stocks [b11] | x=20) |
| m16 | Set target yield @ x litres average                                          | (none stated | x=7800) OR (none stated | x=8500) |
| m16 | Up milk yield target to x litres                                            |                                                                              |
| m17 | maintain production levels                                                    | none stated                                                                  |
| m18 | Increase concentrates to x kg/head                                            | to satisfy [m19] | x=4.5 w=?,1 |
| m18 | Increase concentrates w kg to x kg                                           |                                                                              |
| m19 | increase milk production                                                     | none stated                                                                  |
| m20 | Reduce feeding of silage to x litres                                         | (high wastage [b3] | x=22) |
| m21 | Delete slurry application to wheat (Grp 1)                                   | (*^3k of leaching [b4], also store [b5] has __) OR (not required ) |
| m21 | Remove slurry application in Grp 3                                           |                                                                              |
| m22 | Purchase x heifer calves                                                     | to satisfy [m23] AND to satisfy [m24] | x=25 |
| m23 | future milking                                                               | none stated                                                                  |
| m24 | lift cow herd n's                                                            | none stated                                                                  |
| m25 | Remove fertiliser from group g s (q)                                        | (high nitrates [b6] AND yield [b7] ok | g=3 s=grazing block, q=250kg) OR (none stated | s=April g = wheat, q=? ) |
| m25 | As above – repeat                                                            |                                                                              |
| m25 | Remove s fertiliser on g                                                     |                                                                              |
| m26 | slurry                                                                       | (to satisfy [m11]) OR (filling pit [b5] ) |
| m26 | alter slurry application                                                      |                                                                              |
| m27 | Purchase x m3 silage clamp                                                   | (to satisfy [m28] | x=5000) OR (none stated | x=5000) |
| m27 | Build extra silage pit space x m3                                             |                                                                              |
| m28 | extra storage                                                                | ([future] grass silage harvest[b7]) OR (none stated) |
| m28 | create capacity for store                                                    |                                                                              |
| m29 | Reset target milk yield @ x litres                                          | (not achieving [b8] 8500 [b19] currently | x=8000) |
| m30 | purchase livestock housing x head                                            | (Require | x=50) OR (youngstock n's [b9] growing to limit/capacity[b10] | x=50) OR (allow for young stock n's [b9] entering herd | x=100 ) OR (growing n's [b12] | x=150) |
| m30 | Purchase x head livestock housing                                             |                                                                              |
| m30 | Purchase x cow steading places                                               |                                                                              |
| m30 | Purchase x steading space                                                    |                                                                              |
| m31 | Purchase livestock housing x head                                            |                                                                              |
| m31 | Purchase x head livestock housing                                             |                                                                              |
| m31 | Purchase x cow steading places                                               |                                                                              |
| m31 | Purchase x steading space                                                    |                                                                              |
| m31 | Flip rotation Grp g1 with Grp g2                                             | (address leaching [b4] | g1=1,g2=3) |
|    |                                                                              |                                                                              |</p>
<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>m32.</td>
<td>Sell maize silage (x t) to satisfy [m28]</td>
</tr>
<tr>
<td>m33.</td>
<td>Sell grass silage (x t) (to satisfy [m28]</td>
</tr>
<tr>
<td>m34.</td>
<td>Spread slurry group g to satisfy [m35]</td>
</tr>
<tr>
<td>m35.</td>
<td>Avoid [slurry] spillage none stated</td>
</tr>
<tr>
<td>m36.</td>
<td>Make way for heifers none stated</td>
</tr>
<tr>
<td>m37.</td>
<td>Purchase x m3 slurry pit (all these cows [b12]!</td>
</tr>
<tr>
<td>m38.</td>
<td>Sell hay = x t surplus stocks [b14]</td>
</tr>
<tr>
<td>m39.</td>
<td>Grp g only x cut silage to satisfy [m40]</td>
</tr>
<tr>
<td>m40.</td>
<td>Increase grazing offer none stated</td>
</tr>
<tr>
<td>m41.</td>
<td>heifer calves sell x (price [b17] good</td>
</tr>
<tr>
<td>m42.</td>
<td>Sell calved heifers x (price [b18] good</td>
</tr>
<tr>
<td>m43.</td>
<td>Sell x cows 3rd+ lact (to satisfy [m36]</td>
</tr>
<tr>
<td>m44.</td>
<td>Cull cows sell x (price [b16] good</td>
</tr>
<tr>
<td>m45.</td>
<td>Reintroduced 2nd silage harvest period in Grp 2 area (poor weather [b1] and poor stocks [b11])</td>
</tr>
<tr>
<td>m46.</td>
<td>Redo diets (low silage stocks [b11] )</td>
</tr>
<tr>
<td>m47.</td>
<td>[more] capacity none stated</td>
</tr>
</tbody>
</table>
Follow-up Questions

Issues with Preconditions

On 04/01/04, when selling the cows due to surplus stocks, was this stocks of cows 3\textsuperscript{rd} lact, or all cows?

On 10/10/04, slurry application was altered because of a filling pit. How full does the pit have to be, and/or at what rate does the silage need to be increasing before it is described as 'filling' in this situation?

On 04/02/01 the justification given for deleting slurry to wheat was cut short. The final part of the sentence reads “also store has...”. What was the intended final part of the sentence?

On 02/12/01 when extra housing for livestock was bought, the narrative stated that it was 'required'. Why was it required?

Similarly, on 23/12/01 slurry application was ceased in field group 3, because it was said to be “not required”. Why was it not required?

Resolving Reasonless Motives

For the following days, state the reason(s) for the motives or actions quoted:

NOTE: For some of the actions the reason may seem totally obvious. Even where this is the case, providing a reason is useful.

02/01/00 - Easing management
02/01/00 - Simplifying the system
02/01/00 - Growing wheat as a forage to feed to cows
02/01/00 - Silage feeding during winter period
02/01/00 - Grazing animals during the year
02/01/00 - Purchasing 35 heifers
02/01/00 - Setting target yield to 7800 litres, then on 31/12/00 upping that to 8500 litres
24/09/00 - Maintaining production levels
04/03/01 - Increasing milk yield
08/04/01 - Ensuring future milking
08/04/01 - Increasing herd numbers
13/07/03 - Building 5000m\textsuperscript{3} extra silage pit space
18/08/02 - Creating extra silage storage capacity
12/01/03 - Swapping the cropping plans for groups Grp 3 and Grp1 (rotation)
10/11/02 - Avoiding spillage (overflow) of slurry
22/12/02 - Creating space for more heifers
17/10/04 - Increasing capacity of the slurry store
02/01/05 - Increasing offered grazing
03/04/05 - Removing April fertiliser on wheat

Grounding Beliefs and Actions

On 04/01/09 'poor weather' was described as a reason for re-introducing a second silage cut. Describe in more detail what poor weather is, specifically in terms of rainfall, temperature and/or sunshine.

On 02/01/00 describe in more detail how you went about creating 3 central blocks of field groups. Specifically, how were the shapes, sizes and locations decided.

On 02/01/00 describe in more detail how you went about setting cow grazing groups for the year ahead.

On 02/01/00 describe in more detail how the wheat crop plan for the year ahead was created.
Bibliography


