Abstraction and Modelling of Agri-Food Chains as Complex Decision Making Systems

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Abstract

Agri-food chains are complex systems involving multiple multifaceted firms usually working together within specific industry sectors (e.g. grains, beef, wool, dairy) to satisfy an increasingly globalised market demand for high value food products. In so doing, the groupings of companies involved in an agri-food chain undertake activities that require multidimensional inter-organisational and cross organisational decision-making in the process of adding value to a raw commodity product through the production, manufacturing and distribution stages of the chain. Additional complexity is added by climate variability which impacts randomly and unpredictably on decision making in every component of the chain.

The work outlined in this paper is a pilot investigation looking at a number of approaches to conceptualising and modelling an agri-food chain and its related decision making processes to better evaluate the impact and effects of that decision making and associated information flows across the components of the agri-food chains. The modelling approaches were (i) a multimedia model initially explored as an opportunity to visualise supply and value chain issues for educational purposes; (ii) an agent based model (ABM) using deterministic rules to architecturally synthesise a supply chain, and (iii) a baysian belief network (BBN) which we discuss as an approach for looking at the likelihood of certain decisions being made under certain scenarios.

Introduction

The agri-food sector is a large, multifaceted industry sector that exists worldwide, and involves a range of businesses that create industry specific (e.g. Grains, Sugar Cane, Timber, Dairy, Cattle/Meat, Fruit and Vegetables, Cotton, Wool, to name a few) agri-industry chains that often exist across international boundaries. The businesses involved in such chains tend to deal in low margin commodities where competitive market forces have typically resulted in the cost of production being very close to the value created, thus leaving relatively thin profit margins (Boehlje, 1999). Additionally, raw material production is directly affected by climate and the resulting uncertain weather conditions which very often results in a variable supply of the raw product. Ensuring constant volume, high quality product at the right time and price is thus a key business consideration and involves rigorous supply chain management (SCM) both within the company and between businesses in the industry supply chain (O'Keeffe, 1998; Dunne, 2001, Bryceson & Kandampully, 2004).
Analysis of agri-industry supply chains has thus become a valuable tool in determining where added competitive advantage can be generated for the companies and/or industries involved (Beamon, 1998, 1999). In reality, most supply chain analysis, including the Lean Chain approach of Lammer (1996) and Womack and Jones (1996) tends to focus on measuring stocks and flows of product, information and financial factors - and how managing these in the most efficient way enhances profitability, rather than providing the information necessary for de-

veloping good business strategies that lead to innovative value adding (Govindarajan and Trimble, 2005), competitive advantage (Porter, 1985) and sustainability (Svensson, 2007).

The work outlined in this paper was a pilot investigation looking at a number of approaches to conceptualising and and modelling an agri-food chain and its related decision making processes to better evaluate the impact and effects of that decision making and associated information flows across the components of the agri-food chains. These modelling approaches were (i) a multimedia model initially explored as an opportunity to visualise supply and value chain issues for educational purposes; (ii) an agent based model (ABM) using deterministic rules to architecturally synthesise a supply chain, and (iii)) a baysian belief network (BBN) which we discuss as an approach to look at the likelihood of certain decisions being made under certain scenarios.

(i) Multi-media modelling.

Initially modelling of an agri-food chain was undertaken from the point of view of a multi-media development rather than an abstraction or theoretical modelling exercise per se. The supply chain modelled was the Australian cattle/beef meat industry chain (MLA, 2005). The most common components of this supply chain are shown in Figure 1. The real world issue for the supply chain that was focused upon was information-based decision making and the impact those decisions might have both on the component of the supply chain involved and the other components in the chain. In this pilot project, only one producer, a feedlot, an abattoir, a food processor and the market were defined as components.

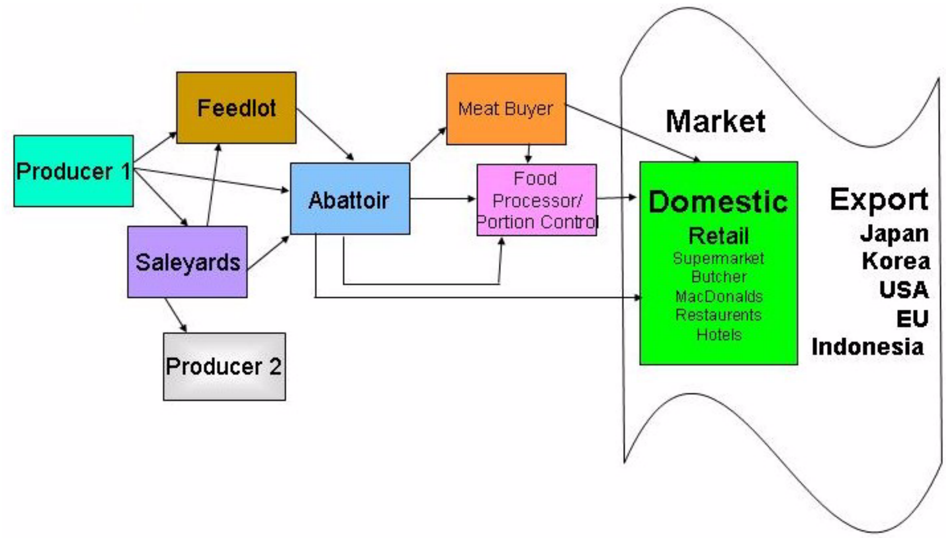

Figure 1. A Generic Beef/Meat Supply Chain in Australia

In the Australian beef meat supply chain the market specifications for the type and quality of animal and/or meat are clearly defined with associated prices attached and thus all components of the chain decide which particular market segment they are aiming for and adhere to delivering the specifications required – if they do not, they risk losing revenue and/or customer. While the beef meat chain is a complicated one with many scenarios and decisions with associated information requirements being involved, the variables chosen for the prototype that were traced throughout VAG were: animal age (days); weight of beast (kg); period of growth (days); price/unit liveweight (c/kg).

Each component of the supply chain (eg Producer, Feedlot, Abattoir etc) was modelled as detailed in Figure 2 with each component having a set of properties and products that could then be used or impacted on by information flows and decisions. A three tier information architecture with a modular, object orientated programming approach was used. Customised XML schema and game application programming interfaces (API) were used to provide easy access in creating and using detailed physical, economic, environmental and social information. In addition, information flows through the communication schema and 'events' of all types - (e.g. decisions, market changes, climatic events such as drought starting or stopping, hazards etc - either randomly timed or controlled), were possibilities with a general structure of target, impact and effect (Figure 2). This approach allowed a degree of scaleability in terms of incorporating multiple supply chains, multiple players and multiple issues (physical, economic, environmental and social) to be incorporated. Customised 3D graphics were developed to illustrate the components and associated decisions being made.

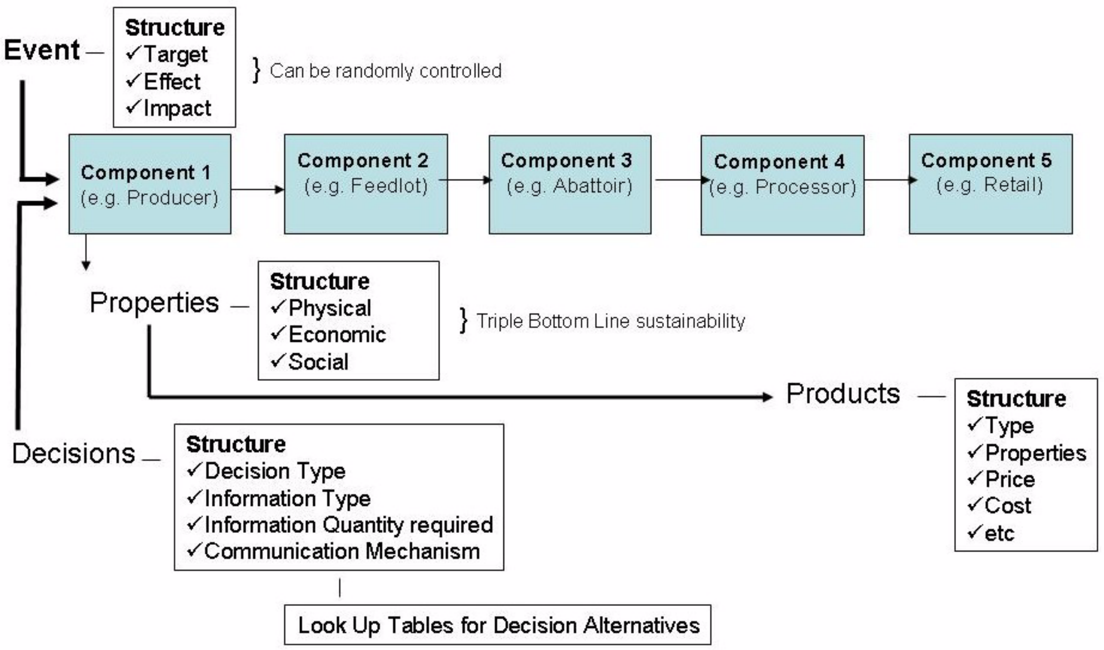

Figure 2. Diagramatic illustration of a component–based supply chain model for a multi-media development

However, the limitations of such a linear modelling approach in wanting to model supply chain issues at a deeper level incorporating "What If" scenarios - and more importantly, wanting to understand any emergent properties/behaviours that might result from decisions being taken at various points in the chain, (with emergence being defined as "the arising of new, unexpected structures, patterns, properties, or processes in a self-organizing system", Choi et al; 2001), meant that the use of a more rigorous approach was deemed necessary. After a thorough search of the literature an Agent Based Modelling (ABM) approach was chosen.

(ii) Agent-Based Modelling of Supply Chains

Supply chains have long been regarded as complicated systems (Jayashankar et al, 1996; Swaminithan et al., 1998) involving both strategic and operational issues along with complex social and functional behaviours. Bonebeau, Dorrigo and Theraulaz (1999), in their book 'Swarm Intelligence' likened a company's and/or an industry's many individual parts to ants in an ant colony. They postulated that by focusing on these distinct entities at 'ground' level, the answers to developing a coordinated overall management strategy could be developed from the 'bottom up' given that such ant colonies were superbly well organised despite having no centralised 'top down' control.

Bornebeau and Meyer (2001) developed this theory further reiterating that supply chains are complex systems comprising many autonomous decision-making 'agents'. Indeed, Choi et al (2001), Pathak et al (2002) and more recently Surana et al (2005) argue the case for them to be regarded as Complex Adaptive Systems (CAS) because individual components or agents within a supply chain can and do, intervene at any point in a meaningful way to change the behaviour of the whole. An agent under these circumstances may represent an individual, a project team, a division, or an entire organization, each agent having varying degrees of connectivity with other agents. The connectivity between agents is what allows information and resources to flow between them. Bonabeau (2002) then argued that if management strategies were to be successfully developed for supply chain systems, the systems themselves should first be modeled using agent-based modeling (ABM) techniques.

ABM is a modeling paradigm in which each "agent" in a system corresponds to an autonomous individual in a simulated domain. The idea is to construct the agents and their attributes and to link them through a set of dynamically interacting communication and behavioral rules to create complexity like that which we see in the real world. The process is one of emergence from the lower (micro) level of the system to the higher level (macro) (Epstein and Axtell, 1996, Li and Sim, 2006).

ABM is a deterministic rules-based approach and allows the modeling of the finer detail of the structure of each component's operation, the signals they pick up and the rules they use to process those signals when making a decision. When different situations are modelled the different ways in which information flows in the chain, and the different sensitivities to that information at each level within the chain, need to be taken into account.

In recent times there has been a plethora of studies and associated literature on multiagent based supply chain logistics handling modeling – mainly from a computational perspective (Dignum et al, 2006). However we are more interested in ABM abstraction and modeling for investigating and visualising business decision making scenarios and related information flows - and to evaluate the impact and effects of such decision making and information flows across components in agri-food chains – an interest which involves different modeling issues. Our theory is that in agrifood chains involving raw material production at source, multiple producers with different production systems and different value and belief systems will make different decisions regarding managing their production and the selling of their product (managing a herd of cattle in our example and then selling that beast into the market), dependent on externalities such as drought or market fluctuations. These different decisions will create ripple effects across all the other components of the beef supply chain – effects which can only be well documented for long term sustainable management if seen many many times – which is only possible using simulation techniques because of the long lag time associated with production in the 'real' chain.

In the current situation being reported on here, agents were defined as different components within the chain (as per Figure 1) which pick up signals such as demand and supply either horizontally across the chain or vertically from within their own component. In this way 'scaleability' was introduced into the model where 'scaleability' is defined as the ability of the simulation to maintain time and spatial consistency on an overall basis, while the number of entities and accompanying interactions increase, thus enabling a more detailed model to be incorporated. This approach allows the discernment of where and when emergent phenomenon/ behaviours start to emerge (Bottcher et al, 2006).

The software iThink TM was used to set up “Agents” (Producer, Feedlot, Abattoir and Market) each with their own independent decision-making rules. The information flow rules that were then created allowed information to pass from one component in the chain to another allowing, for example, a feedlot to make a ‘decision’ to fatten a particular type of animal according to a demand signal from an abattoir and a supply signal from a producer.

While only one Producer, Feedlot, Abattoir and Market component in the Australian beef supply chain was originally developed as agents in this pilot, the approach allows any number of agents to be added – each with its own decisions and rules. Thus there could be fifty producers, ten feedlots and five abattoirs involved in a real chain and all making their own decisions based on the same or similar information that can be modeled using this approach. Additionally, other supply chain components could also be added such as saleyards, animal feed companies, chemical suppliers, smallgoods processing companies, retail etc, each with their own linkages creating a supply network which is more realistic in its complexity.

The following pages show a series of figures where the pilot ABM model is depicted graphically. Each agent (= supply chain component) is outlined in a box. There are also a number of associated models located below the main component models also depicted in boxes. Figure 3 shows, for the sake of completeness, the overall ABM model of a single producer, single feedlot, single abattoir and the market. The model detail is not possible to see at the scale necessary to display on a page. However, each component in the chain has up to 3 sub agent models (in this relatively simple model only – others can be added). For example, each component has an associated economics model, but the single producer model also has an associated ‘sustainability model’ (drought, pasture quality and stocking rate) and cattle growth rate model (including supplementary feeding). The producer economics model captures the time it takes to grow an animal, costs involved and sale price.

Figure 4 shows an enlarged version of part of the producer model where a decision to sell cattle 20-30 months of age is made depending on market demand and the profitability to the producer.

Figure 5 shows an example of how a rule within the feedlot model reflects the criteria associated with a decision by thefeedlot to buy animals from a producer.

Figure 6 shows an example of a ‘What If’ scenario where the price of grain is altered and how this impacts on feedlot profitability given everything else remains the same.

However, as discussed, supply chains are not linear – they are highly complex networks of components, information flows and decisions. While ABM enables the detailed modelling of decisions and flows within a supply chain, as a rules-based or deterministic paradigm it will not allow the accommodation of uncertainty into a model. This is a problem since to quantify or to manage risk, for example, both within, and between, supply chain component variability and uncertainty needs to be incorporated. There are many probabilistic modelling approaches that might be employed to do this – in the case outlined here Baysian Belief Networks (BBNs) were investigated as an approach to enable probabilistic scenarios to be developed that could enable the stochastic behaviors of a supply chain over time to be modelled.

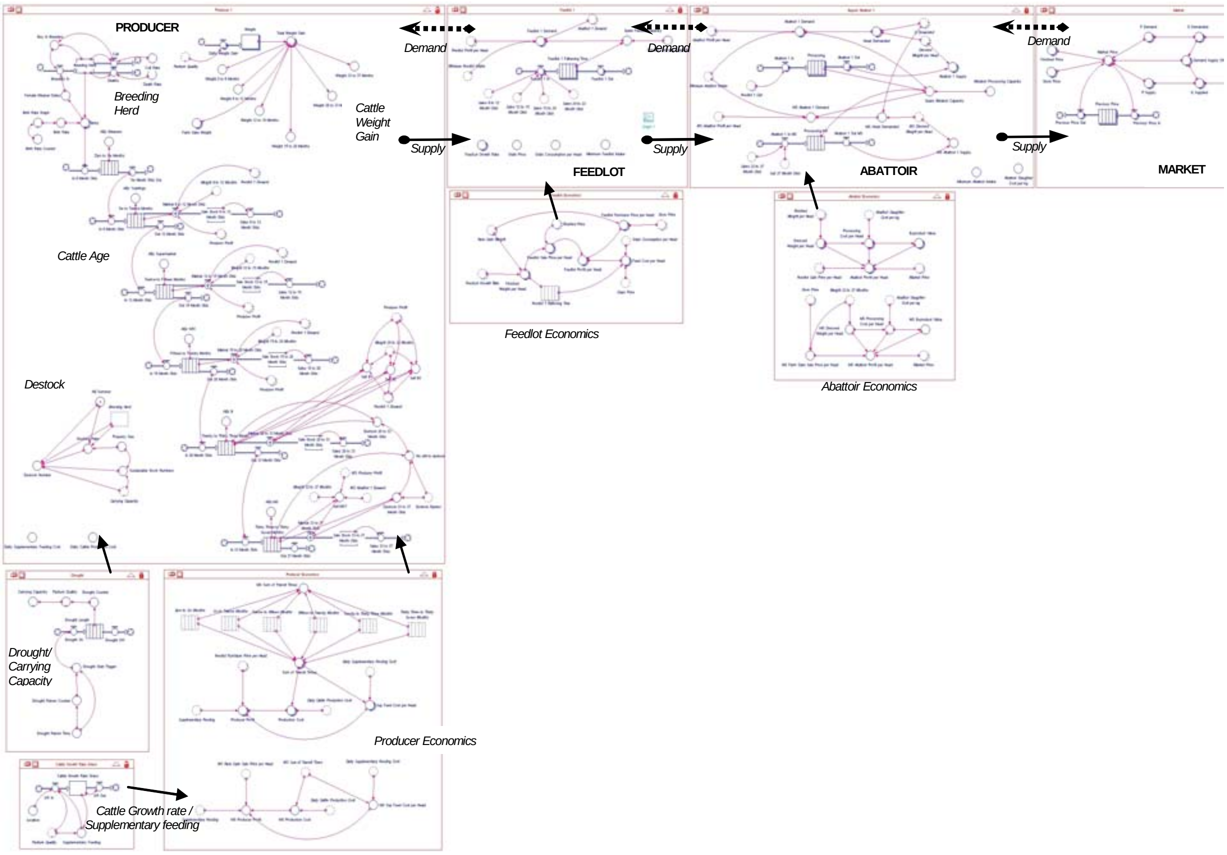

Figure 3. Graphical depiction of an ABM model of a single producer, single feedlot, single abattoir and the market. The basic premise in this example is: A Rational producer making decisions based on profitability, a demand driven chain, and a basic market supply/demand model.

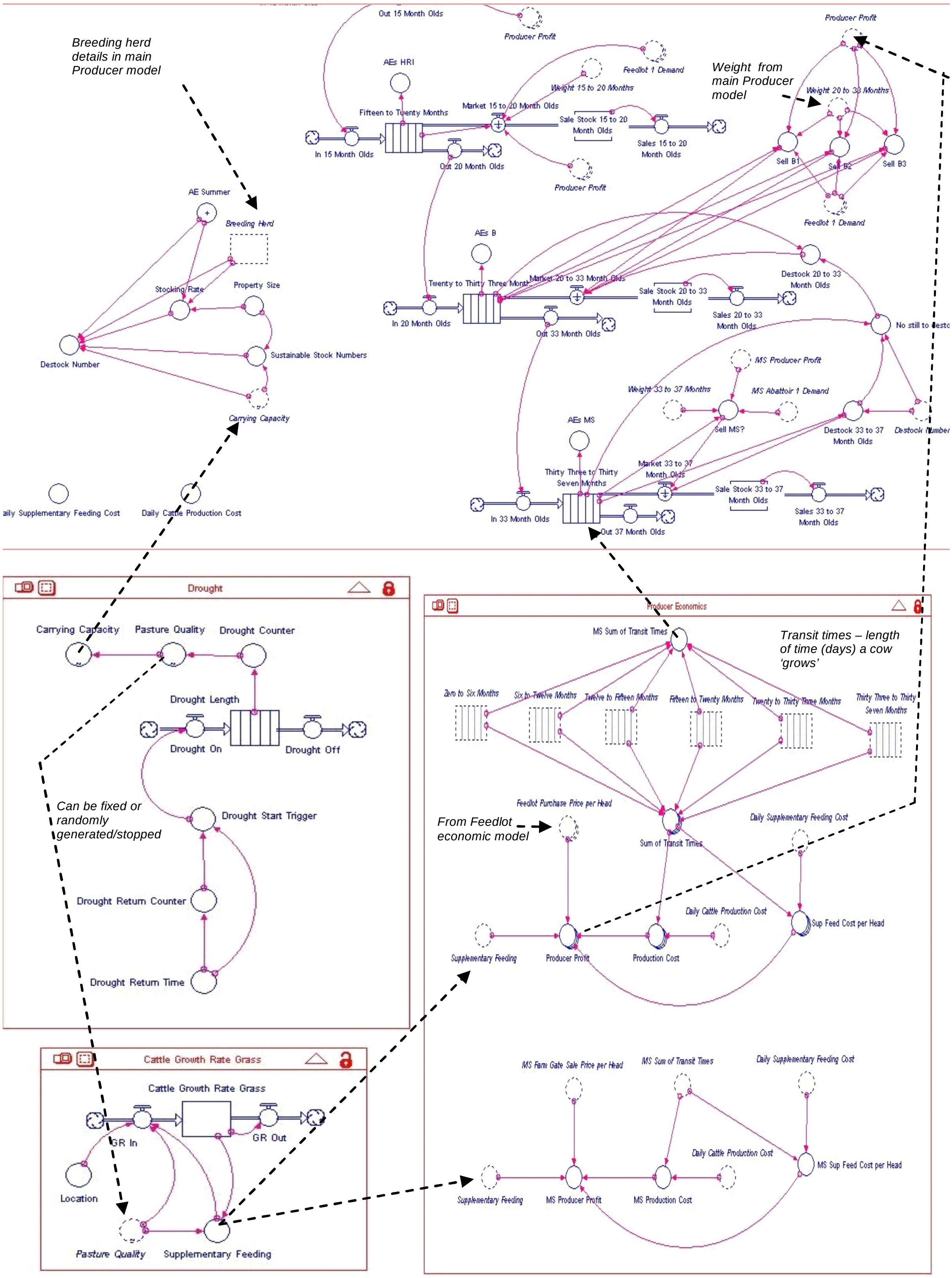

Figure 4. Decision to sell cattleof 20-30 months depending on market demand and profitability to producer. All circles representing variables and having dotted lines come from another agent. Cattle growth rate used dependent on location and pasture quality

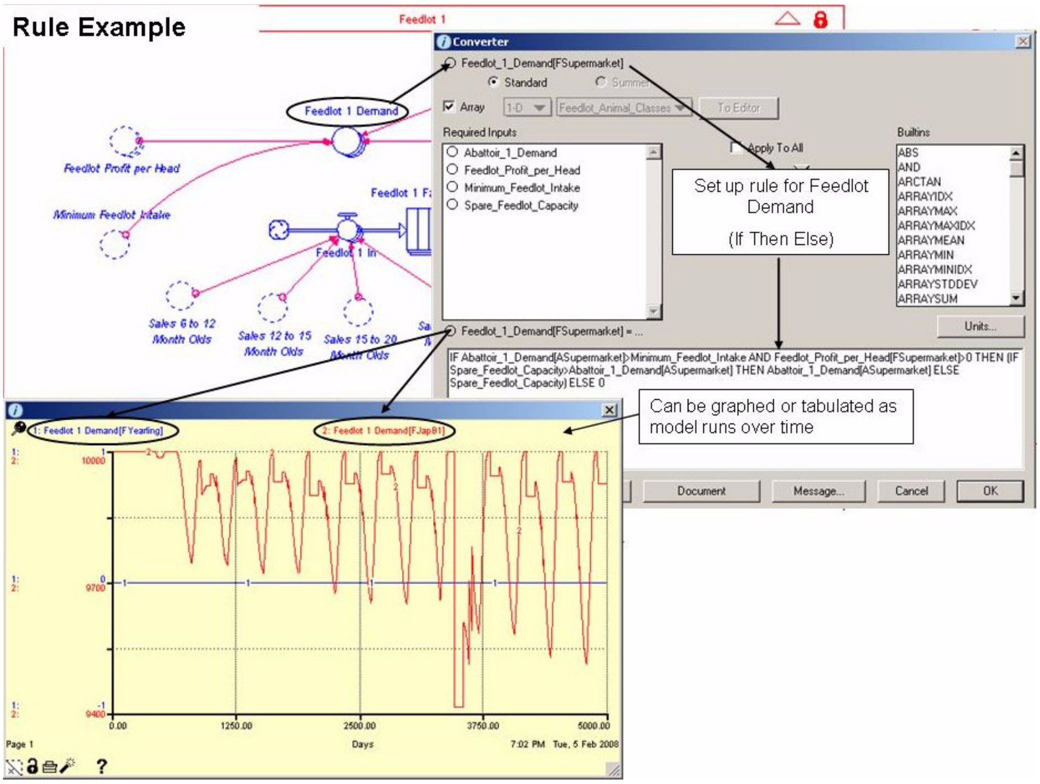

Figure 5. Example of a Rule within the Feedlot model showing the criteria associated with a decision by the Feedlot to buy animals from a producer. Criteria are feedlot demand for animals meeting the selection criteria for supermarket quality, abattoir demand and feedlot pofitability

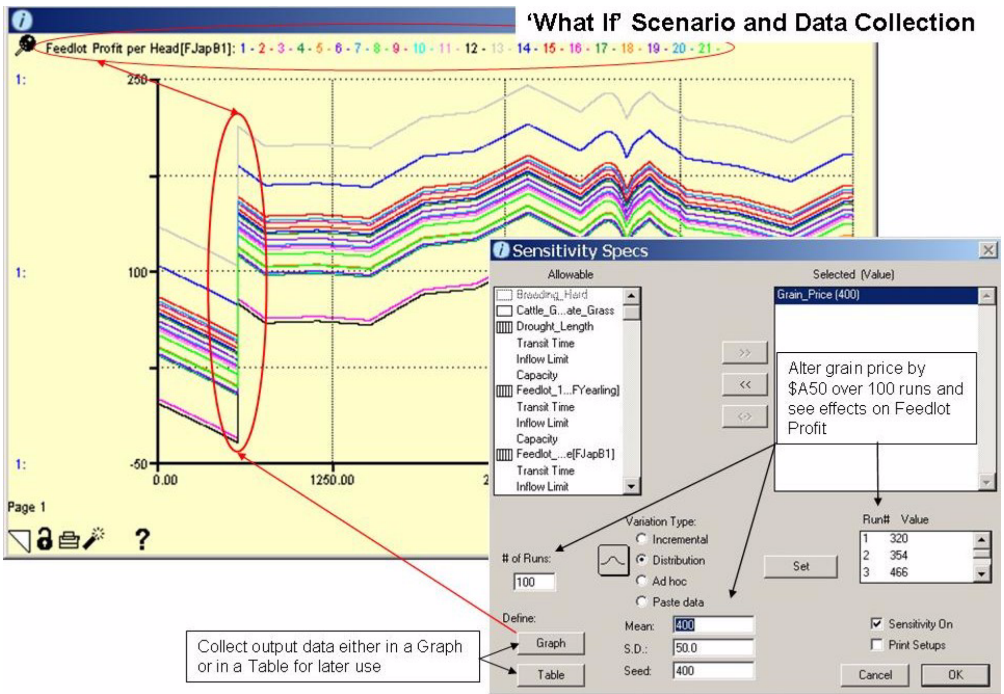

Figure 6. An Example of a 'What If' scenario where the price of grain is altered and the impact on Feedlot profitability is calculated over a long period of time - in this case 30(100x the model timeline)

Baysian Belief Modelling

Baysian Belief modelling is an approach to modelling that can both graphically and probabilistically represent correlative and causal relationships among variables (Charniak, 1991). It involves describing a system in terms of variables and linkages that depict the probabilistic independent relationship between variables at a level appropriate to the decision making. This is achieved through representing linkages as conditional probability tables and dynamically spreading the probabilities through the network to give the likelihood of variable outcomes.

Baysian Belief Networks (BBNs) are the graphical models that provide a simple representation of the conditional probability distributions associated with several variables (Marcot, 1998; Marcot et al, 2006). Each variable is represented as a ‘node’ and each link is represented as an ‘arc’. Two variables (nodes) are unconditionally independent if they have no common ancestor variables.

Because a Bayesian network is a complete model for the variables and their relationships, it can therefore be used to answer probabilistic queries about them (Charniak, 1991; Marcot, 1998; Lauria and Duchessi, 2006). For example, the network can be used to find out updated knowledge of the state of a subset of variables when other variables (the *evidence* variables) are observed (Cain, 2001). As such, they could depict the influence of different managerial approaches and/or decisions. Additionally, since a Bayesian network is dynamic and interactive, if a network previously developed does not fit a user's conceptual understanding of the system, it can be adapted quickly and simply to the users knowledge.

BBN modelling has been used quite extensively to model various situations where uncertainty plays a major part in management decision making scenarios – for example in natural resource management (Tucker et al, 1997; Cain et al, 1999; Cain, 2001; Robertson and Wang, 2004, Nyberg et al, 2006; Marcot et al, 2006; McCann et al, 2006; Smith et al, 2007; Aalders, 2008). It has also been used in business decision making for example in IT systems management (Gran, 2002; Lauria and Duchessi, 2006), risk management (Alexander, 2000; Roelen et al, 2004; Neil et al, 2005), bankruptcy predication (Lili and Shenoy, 2007), customer service satisfaction (Anderson et al, 2004), and in various aspects of food production (Fearn, 2003, Stein, 2003; van Beek, 2003), and in food product design (Corney, 2000; Jongenburger, B., 2005). It is thus useful and valid to investigate it’s use for agri-food supply chain management modeling as a complimentary approach to ABM in incorporating uncertainties into the modeling.

Netica ^{TM} software (Norsys Software Corporation, 1998) was used to
set up a simple BBN representing the question: “What does it take (in relation to the ABM modelled beef supply chain discussed here) to create a healthy supply chain?” Figure 7 shows a BBN constructed for this purpose. Populating the conditional probability table for the supply chain components involved (Table 1) was undertaken using expert knowledge. To maintain logical consistency in the elicited probabilities, a procedure similar to that described by Cain (2001) was adopted. Specific scenarios were selected: these were: (a) the best-case scenario where all of input variables were in the best state; (b) the worst-case scenario where all of the input variables were in the worst state, and; (c) scenarios where only one input variable was not in the best state. Probabilities were elicited for these scenarios and were then used as reference points for eliciting probabilities for the remaining scenarios in the conditional probability table.

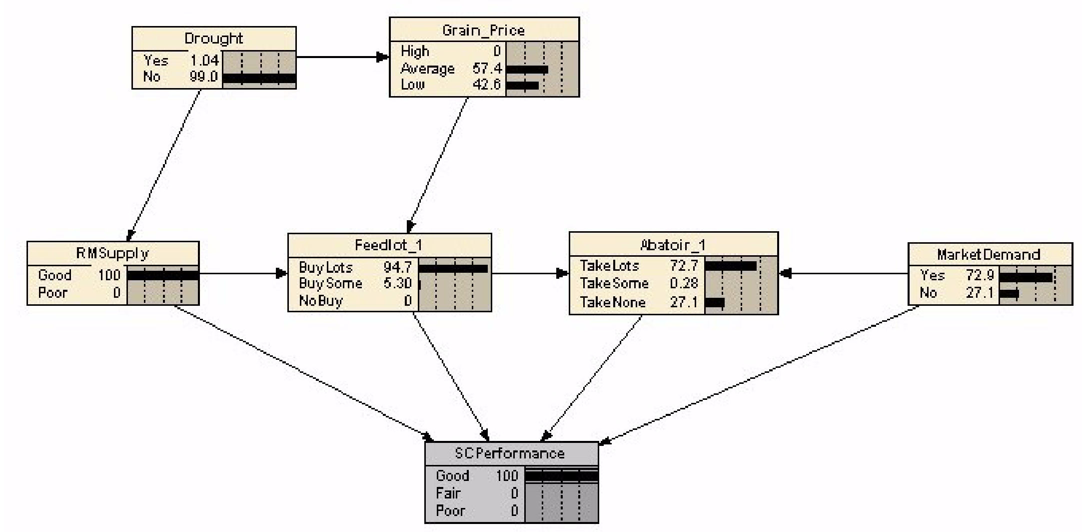

Figure 7. Shows a BBN constructed to answer the question: "What does it take (in relation to the ABM modelled beef supply chain discussed here) to create a healthy supply chain this purpose.

Table 1. Part of the conditional probability Table set up for the variables shown in Figure 7.

Feedlot_1	Abatoir_1	MarketDemand	RMSupply	Good	Fair	Poor
BuyLots	TakeLots	Yes	Good	100.00	0.000	0.000
BuyLots	TakeLots	Yes	Poor	0.000	20.000	80.000
BuyLots	TakeLots	No	Good	80.000	20.000	0.000
BuyLots	TakeLots	No	Poor	0.000	20.000	80.000
BuyLots	TakeSome	Yes	Good	50.000	30.000	20.000
BuyLots	TakeSome	Yes	Poor	0.000	16.000	84.000
BuyLots	TakeSome	No	Good	80.000	20.000	0.000
BuyLots	TakeSome	No	Poor	0.000	20.000	80.000
BuyLots	TakeNone	Yes	Good	64.000	36.000	0.000
BuyLots	TakeNone	Yes	Poor	0.000	20.000	80.000
BuyLots	TakeNone	No	Good	40.000	40.000	20.000
BuyLots	TakeNone	No	Poor	0.000	16.000	84.000
BuySome	TakeLots	Yes	Good	60.000	30.000	10.000
BuySome	TakeLots	Yes	Poor	0.000	18.000	82.000

Outcomes

What we present here are very early outcomes of conceptualizing and modelling the Australian Beef Chain using ABM and BBN approaches. At this stage the results have really provoked more questions than answers – however what can be said, is that ABM appears to be a very adequate tool in enabling the conceptualization of an Agrifood chain as a series of agents that can and do, make individual decisions. Running the ABM model multiple times, does show that there are some emergent behaviors that occur, particularly when 'What If' scenarios are created, but understanding these and working out what they mean overall in the long term to the supply chain, is still being investigated.

In terms of increasing complexity in the model, it is very possible to incorporate additional components at each stage of the chain so as to increase the model's validity. However it should be noted that once the numbers of individual components (agents) at each point in the chain is increased above one, the complexity both in terms of the actual modelling and in the data needed to ensure rigorous rule creation, is very high.

BBN also appear in these early stages to be a useful modelling approach and tool to find out what are the most important properties related to the perceived and experienced health of the supply chain. The results can be a ranking of the variables, showing which variables have the highest impact on the health of the supply chain. They can also be used to refine probability information that can then be included in a rules based system. Work continues in order to strengthen the case for their use, particularly in relation to obtaining and using “soft” or subjective data associated with decision-making variability’s that might be included in updating the ABM model. Further work also involves:

- ABM and BBN modelling of multiple components (e.g. 50 producers, 3 saleyards, 5 Feedlots, 10 abattoirs, 5 retailers, etc) as individual agents in chain/network and linked together to look at overall supply chain health. This will require expert advice to tighten rules/probabilities, and additional information for the associated additional decisions;
- Modelling different supply and value chains and complex networks incorporating governance issues, cultural issues, sustainability issues, trust and eReadiness modelling, as a tool for testing performance systems and metrics.

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