ICIS 2005 Proceedings

International Conference on Information Systems (ICIS)

December 2005

Intelligent Agents as a Modeling Paradigm

Kafui Monu
University of British Columbia

Carson Woo
University of British Columbia

INTELLIGENT AGENTS AS A MODELING PARADIGM

Kafui Monu, Yair Wand, and Carson Woo
University of British Columbia
Vancouver, BC Canada
kafui.monu@sauder.ubc.ca **Yair.Wand@ubc.ca** **Carson.Woo@ubc.ca**

Abstract

Intelligent software agents have been used in many applications because they provide useful integrated features that are not available in "traditional" types of software (e.g., abilities to sense the environment, reason, and interact with other agents). Although the usefulness of agents is in having such capabilities, methods and tools for developing them have focused on practical physical representation rather than accurate conceptualizations of these functions. However, intelligent agents should closely mimic aspects of the environment in which they operate. In the physical sciences, a conceptual model of a problem can lead to better theories and explanations about the area. Therefore, we ask, ***can an intelligent agent conceptual framework, properly defined, be used to model complex interactions in various social science disciplines?***

The constructs used in the implementation of intelligent agents may not be appropriate at the conceptual level, as they refer to software concepts rather than to application domain concepts. We propose to use a combination of the systems approach and Bunge's ontology as adapted to information systems, to guide us in defining intelligent agent concepts. The systems approach will be used to define the components of the intelligent agents and ontology will be used to understand the configurations and interrelationships between the components. We will then provide a graphical representation of these concepts for modeling purposes.

As a proof of concept for the proposed conceptual model, we applied it to a marketing problem and implemented it in an agent-based programming environment. Using the conceptual model, the user was able to quickly visualize the complex interactions of the agents. The use of the conceptual representation even sparked an investigation of previously neglected causal factors which led to a better understanding of the problem. Therefore, our intelligent agent framework can graphically model phenomena in the social sciences. This work also provides a theoretically driven concept of intelligent agent components and a definition of the interrelationships between these concepts. Further research avenues are also discussed.

Keywords: Conceptual modeling, intelligent agents, agent-based simulations

Introduction

Some researchers have noted that agent-based simulations can be used to solve complex problems in business (Langdon 2005) and other research areas (Tesfatsion 2002). However, no standard method for creating these models exists, and the definition of agent components (even the nature of an agent) is not clear (Drogoul et al. 2002).

Multi-agent systems have been used to simulate the interaction within large groups of players in various settings (Drogoul et al. 2002). These simulations are used to understand the complex patterns that can emerge from the actions and interaction of individuals. Even though the tools to create these systems have become simpler, the task of building a good agent-based simulation is still complicated, due to the increased complexity of the modeled interactions.

In the area of agents, researchers have suggested that simulation building be split into three roles: thematician, modeler, and computer scientist (Drogoul et al. 2002). The thematician creates a domain model which describes how the interactions in that specific domain work; this is also called a theoretical model. The modeler creates the design model, which consists of formal refinements of the theoretical constructs.

A survey of existing agent methodologies (Arazy and Woo 2002; Shehory and Strum 2001) shows that many of these methodologies typically emphasize the computerized implementation aspects of agents. This can cause problems in the development of agent-based simulation systems where, first, one needs to understand the modeled domain.

In the paper, we address the question: *Can an intelligent agent framework, properly defined, be used to model complex interactions in various social science disciplines?*

Specifically, we are proposing a modeling system that will handle complex agent interactions and act as a bridge between the thematician and modeler.

After a brief review of related work, we create a mapping between a set of agent concepts (as identified by Arazy and Woo [2002]) and a set of theoretical constructs. Once defined, these concepts are then converted into a graphical representation. It is then tested by developing a representation of, and implementing a system to solve, a marketing problem. The results of the implementation are briefly discussed. The final section concludes our work and suggests future research direction.

Related Work

There are some areas that have used software agents in modeling the environment. One such area is complex adaptive systems (CAS). The CAS area's main goal is to study the emergent behavior of a system comprised of simple agents which react to the environment, much like animals, rather than learn and reason like intelligent agents (Holbrook 2003).

A field that uses simple, and intelligent, agents is the area of agent simulation. Agent simulation can be used to model phenomena in various disciplines, from chemistry to sociology. However, researchers do not have the tools to communicate the conceptual level of their problem (Arazy and Woo 2002). Currently in the subfield of agent simulation called agent-based computational economics (ACE), researchers communicate models using pseudo-code produced on an *ad hoc* basis (Kirman and Vriend 2002; Tesfatsion 2005) or are proposing using an actual programming language to communicate their models (Terna 2002). Unfortunately, these languages would be at the design level and may be too detailed to act as a conceptual model.

Much work has also gone into developing various design level methodologies for software agents like GAIA, MaSE, AUML, and others (Arazy and Woo 2002). The strengths and weaknesses of these methodologies will be discussed later.

As mentioned previously, various works have employed intelligent agents in simulation models. However, very few research fields have used intelligent agents for conceptual modeling. A review of the literature shows that the main users of intelligent agent modeling are supply chain management (SCM) researchers (Kim et al. 2002; Nagoli and Biegel 1993). Recently, van der Zee and van der Vorst (2005) developed a modeling framework for supply chain management specifically to act as a *communicative means* between the analyst and problem owners. Along with the framework, they also developed a visual modeling tool to help the analyst to communicate the model to problem owners. However, their constructs are supply-chain specific and are focused mainly on the flow of goods and information, since this is the main area of interest for supply-chain analysis. What is needed is a more general conceptual model of intelligent agents that can be used to analyze problems not necessarily in a limited field (such as supply-chain management).

What Is an Agent?

To develop a conceptual model of intelligent agents, we need to identify a basic set of agent concepts. Sikora and Shaw (1998) developed a framework for agents which stated that an agent was a component in a system and performed specific activities when it was in a specific state. The authors do not, however, go into the development of agent constructs. Arazy and Woo (2002, p. 229) state that "there is no theory to guide the selection of constructs and models for representing" agent components. Nevertheless, this has not stopped the use of agent concepts. Some of the current concepts used to describe intelligent agent structures and processes include goals, beliefs, knowledge, reasoning, plans, and learning. While these terms are commonly used, different definitions are applied for each concept (Wooldridge 2002). This leads to unclear general definitions that try to include all idiosyncratic meanings of the terms. Even though the general concepts are vaguely described, it is apparent that they are interrelated. For example, learning, by definition, has some effect on beliefs (Arazy and Woo 2002).

Intelligent agents are used to represent phenomena in the real world. Therefore, our methodology must not only allow us to understand intelligent agents, but also make sure that these agents accurately reflect the world. One such framework is systems theory. One of the main strengths of systems theory is the ability to identify the components of a phenomenon (system) and study how those components work together to determine the system's behavior (Miller 1978). It is proposed that an intelligent agent can be conceptualized as a system, and that the systems approach can be used to refine and define intelligent agent concepts.

Systems Approach

A system can briefly be described as "a set of interrelated elements" (Ackoff 1971, p. 662). The main assumption behind systems thinking is that all things have an objective. Once that objective is found, then the different components of the system that act to achieve it can be identified (Churchman 1979). An intelligent agent, according to Wooldridge (2002), should be adaptive, reactive, communicative and autonomous. Therefore, if we break the "agent system" down it means that the agent needs to read the environment, "think" about how to achieve its goal, and then have the ability to interact or communicate with the environment, to be effective. This means that the agent can be thought of as a feedback system (see Figure 1).

A feedback system is a control system comprising a sensing component, a control apparatus, and an effector which changes the environment.

We propose that an intelligent agent can be considered a feedback system which has an objective, learns from the environment, and chooses the best process to achieve that objective.

Now that the type of system has been identified, the components of the intelligent agent system also need to be identified. Miller's (1978) work describes the needed subsystems for intelligent simulated behavior as shown in Figure 2. The model has a receptor (defined as the input transducer and decoder), a control apparatus (the associator, memory, and encoder components) and an effector (output transducer).

We propose that on a conceptual design level, the input transducer and decoder (receptor) can be taken as given. They will be designed to accurately interpret specific variables in the environment. However, the operations of the associator and memory subsystems, as well as the functions of the output transducer, need to be specified in the design phase. We term the combination of associator and memory as the *simulator*, as it needs to mimic phenomena in the controlled domain, while the *effector* is the part of the agent that can make changes in the environment. We propose that an intelligent agent is a system made up of a simulator and effector. However, to gain a better understanding of how this system works to produce intelligent agent behavior, we will use the Bunge-Wand-Weber (BWW) ontology.

Formal Definition of the Intelligent Agent System and Subsystems

Using systems theory, we have been able to identify the necessary components for an intelligent agent. However, to fully understand a system, its components' processes and how those processes interact need to be investigated. We will use the ontological approach to add semantics to the interrelationships, configurations, and transitions of the simulator, effector, agent, and environment.

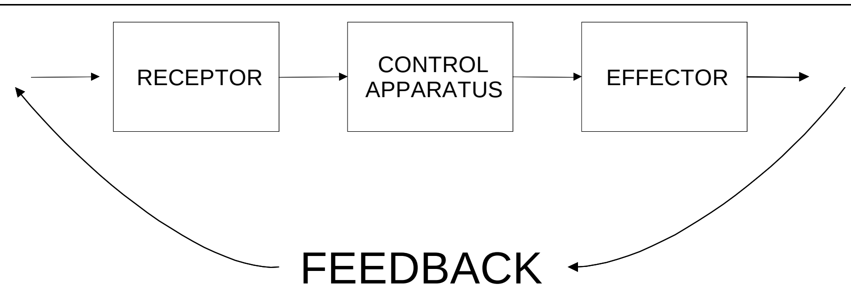

Figure 1. Simple Feedback System (Figure 7.2a in L. von Bertalanffy, *General Systems Theory: Foundations, Development, Applications,* George Braziller, New York, 1968, p. 162)

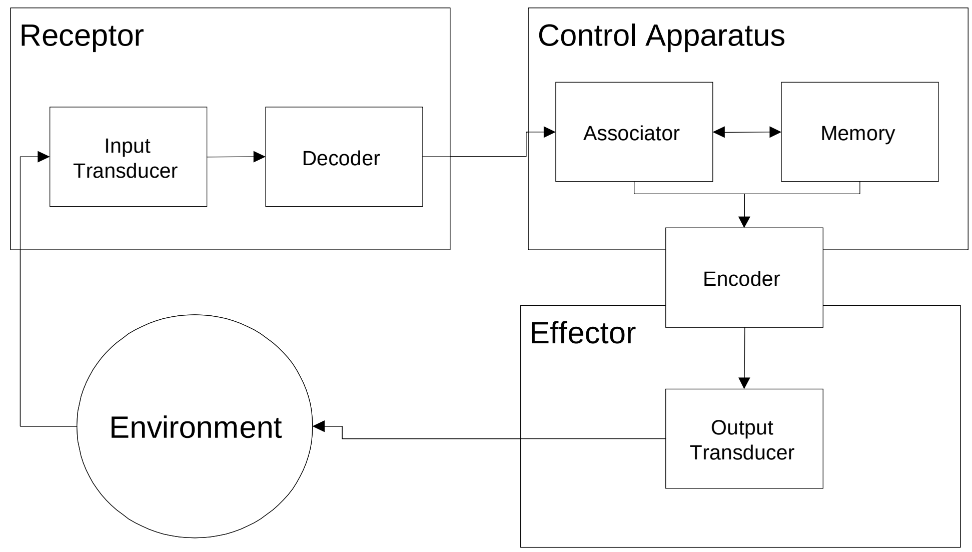

Figure 2. Subsystems of Simulated Intelligent Behavior (Adapted from J. G. Miller, *Living Systems*, McGraw-Hill, New York, 1978)

Table 1. Ontological Constructs Used in the Definition of Agent Concepts

Ontological Construct	Definition (from Wand and Weber 1995)	Symbol
Thing	The elementary unit in the BWW ontology. A composite thing may be made up of other things (composite or primitive).	T
Property	A property is modeled via a function that maps the thing to some value. A property that is inherently a property of an individual thing is called an intrinsic property. A property that is meaningful only in the context of two or more things is called a mutual property.	Intrinsic : p(T) Mutual : p(T1,T2)
Attribute	An attribute is a human representation of a property of a thing.	A_p
State	The vector of values for all property functions of a thing.	$s(T) = A_1(T) \ldots A_n (T)$
State space	The set of all possible states	S
Transition Law	The rules governing the changes of state over time	L: S ➔ S
State law	Restricts the values of the property functions of a thing to a subset that is deemed lawful because of natural or human laws.	L_T
Transformation	A mapping from a domain comprising states to a co-domain comprising states.	
Lawful Transformation	Defines which events in a thing are lawful.	
Stable State	A state in which a thing, subsystem or system will remain unless forced to change by virtue of the action of a thing in the environment.	L(s) = s
Unstable State	A state that must change into a new state.	$L(s) \neq s$
Event	A change of state of a thing. It is effected via a transformation.	$e(T) = <s_1,s_2>$

The area of ontology deals with modeling the existence of things in the world. Using the ontological approach, we defined the relationships between the agent system and its subsystems. Specifically, we used an ontological approach that is an adaptation of Bunge's (1977, 1979) ontology applied to information systems (Wand and Weber 1990, 1995), or the BWW ontology. This ontology provides specific constructs for defining information system components and processes, and includes many of the concepts found in systems theory, making it useful for modeling the components and processes of a system. The reasons for using this ontology were that it is highly formalized and was specifically developed to represent information systems. The ontological concepts and premises aided us in creating clear relationships and definitions of intelligent agent terminology. Table 1 shows the ontological constructs of the BWW ontology.

So to begin defining the intelligent agent, let W be the agent's world, Sim be the agent's simulator, and E be the agent's effector, and let "➔" mean *cause*. According to our model, a change in the *world* can effect a change in the simulator, which may cause a change in the effector. This in turn, will lead to a change in the world. More formally,

$$e(W) \rightarrow e(Sim) \rightarrow e(E) \rightarrow e(W)$$

The way a change in one thing causes a change in the other can be modeled ontologically as follows: assume an event occurs in W. If as a result a mutual property of W and Sim changes, then Sim might reach an unstable state which will cause it to change again. This new change might cause a mutual property of Sim and E to change. Thus, a change in W will be propagated to a change in E via Sim. How Sim and E will change states depends on their laws. Specifically, for a given thing, an event starting in an unstable state is determined by the transition law of the thing, $e(T) = <s(T),s'(T)>$ where $s'(T)=L_T(s(T))$ or, briefly:: $e = <s,L(s)>$ where e, s, and L all relate to the same thing.

The propagation of changes can be modeled as

$$e(T1) = <s_1(T1),s_2(T1)>$$

Let C(e) denote the set of attributes that change in an event e. A change will propagate from a thing T1 to a thing T2 iff there exists a mutual property p(T1,T2) such that $A_p \in C(e(T1))$. Specifically, for our model of agents, the propagation of changes can be described as

(1) An event e(W) occurs.
(2) For e(W) $\exists p(W,Sim) \in C(e(W))$ and the state of Sim after e(W) is unstable bringing about an event e(Sim): $e(W) \rightarrow e(Sim)$.
(3) For e(Sim) $\exists p(Sim,E) \in C(e(Sim))$ and the state of E after e(Sim) is unstable bringing about an event e(E): $e(Sim) \rightarrow e(E)$.
(4) For e(E) $\exists p(E,W) \in C(e(E))$ bringing about an event e(W): $e(E) \rightarrow e(W)$

The description uses ontological concepts to model an agent's behavior. However, computer and cognitive science researchers refer to the actions of intelligent agents using different terms. Therefore, we sought to link our ontological description of agent behaviour to concepts previously used in the agent literature.

Figure 3 shows, graphically, the different concepts and how they relate to the world, the simulator, and the effector. An italicized concept is dynamic and directly related to the static concept above it. Perception is tied to learning, reasoning is tied to procedures, and actions are tied to resources. These terms are not new but when used in various agent methodologies their definitions have been inconsistent and vague (Arazy and Woo 2002).

With the concepts in Figure 3, we can describe intelligent behavior by saying that perceptions affect the beliefs of the agent which can then lead to the agent trying to achieve a specific goal. The agent can then go through a set of procedures which will, according to reasoning, lead to achieving its goal. It can then try to turn those procedures into their respective actions by using its resources, if it has the capabilities to do so.

In Table 2, we define the agent concepts using the BWW ontology definition of intelligent agent behavior.

By conceptualizing the intelligent agent as a system, we were able to identify its components and processes. Since the conceptual framework defines the intelligent agent's components and its mode of interaction with the world, we now have a framework that incorporates a set of concepts needed to talk about an agent which interacts with, models, and acts upon the world. However as stated previously, these terms and concepts are not new and have been used in other methodologies.

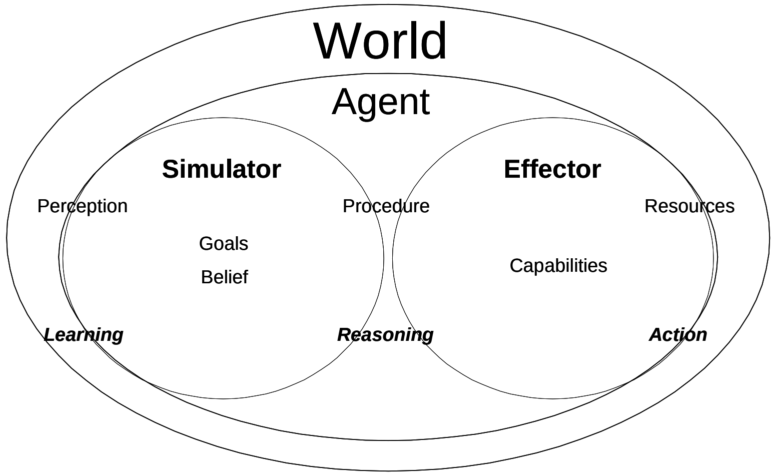

Figure 3. Representation of Intelligent Agent Concepts

Table 2. Agent Concepts and Definitions

Intelligent Agent Concept	Proposed Ontological Definition	Notes
Perception	**p(W,Sim)**. Mutual property between the world and the simulator.	If something occurs in the world without the agent perceiving it, it will be impossible for the agent to know about that event.
Learning	**e(W) such that $\exists A(W,Sim) \in C(e(W))$ and, the new state of Sim is unstable (leading to further changes of Sim)**. A change in the mutual property of the world and the simulator and a following event (lawful transformation) in the simulator.	The mechanism which enables the world to change the simulator. An agent can only learn if the change is aligned to the laws of the simulator.
Belief	**A specific p(Sim).** Intrinsic property of the simulator.	Changes in beliefs are governed by laws or assumptions L(Sim), but may not reflect the reality of the world
Goals	**$s \in S(Sim)$, $L_{Sim}(s)=s$.** A stable state of the simulator	If the agent is agitated the simulator will try to find a procedure which will lead to the “goal” scenario.
Procedures	**p(Sim,E).** A mutual property between the simulator and effector	It is possible that the agent will want to perform an action but may not be able to do so.
Reasoning	**L_{sim}**. A lawful transformation of the simulator and possibly a change in the mutual property of the simulator and effector **e(Sim) such that $\exists A(Sim,E) \in C(e(Sim))$.**	Specific conditions need to hold before the agent will reason that a procedure needs to be activated.
Capability	**p(E), $\exists s \in S_W$ $L_W(s) \neq s$, A_p and $\exists A(E, W) \in C(e(E))$,** An intrinsic property of the effector which changes as the result if certain transformations in the effector occur.	To perform certain actions (use resources) the agent must have some internal capabilities.
Resource	**p(E,W).** Mutual property of the world and effector.	To use a resource from the environment, a mutual property between the effector and environment must exist.
Action	**L_E , e(E) such that $\exists A(E,W) \in C(e(E))$.** A lawful transformation of the effector which changes a mutual property of the world and the effector.	Certain properties of the effector (capabilities) need to be present before the event can take place.

Table 3 describes how these different methodologies deal with modeling aspects of intelligent agent concepts. The references for AUML, GAIA, and MaSe can be found in Arazy and Woo (2002). Information on Tropos, Prometheus, and ROADMAP can be found Giunchiglia and Perini (2002), Padgham and Winikoff (2002), and Juan et al. (2002), respectively.

Table 3 shows that these methodologies cannot model all aspects of intelligent agents but our method can. Perceptions model the agent's observations. The belief and learning concepts model the agent's changing world view, while the action and resource concepts model the agent's impact on the world. Interaction between the agent and/or environment is handled by the resource and perception concepts. When an agent's resource is another agent's perception, the two agents are interacting. Finally, the agent's goal is defined by the goal concept, and the reasoning concept makes it possible to specify how the agent will react to a change in the environment to achieve its goal.

Table 3. Modeling of Intelligent Agent Concepts with Existing Agent Methodologies

	Receiving Observations/Signals	**Agent's World View**	**Dynamics of the Agent's World View**	**Representation of Actions**
AUML	Agent receives messages from other agents	Defined as communicative acts that are modeled by classes and objects	None	Action is represented as the output of the agent, coupled to a message
Tropos	None	None	None	None
Prometheus	Percepts which the agent acquires from the environment	Data objects which the agent has access to	None	Modeled in the interaction diagram; no mention of constraints
GAIA	Permissions the agent reads from the environment	None	None	In the Activities and Protocols section of the role model (no constraints)
ROADMAP	Permissions the agent reads from the environment	None	None	In the Activities and Protocols section of the role model (no constraints)
MaSE	None	None	None	Tasks and protocols, no mention of constraints
	Consequences of action	**Interaction**	**Agent's Purpose**	**Intentional Thinking**
AUML	State changes in the agent. No impact on the environment	Only amongst other agents and not the environment	None	Proactive actions which are taken when certain conditions are met
Tropos	None	Agent to agent interaction modeled through Goal dependency; interaction with environment modeled through goals	Through goal diagram	None
Prometheus	None	Data objects to which the agent has access	None	None
GAIA	Permissions the agent can change	In interaction diagram as a process	Defined in the role diagram	None
ROADMAP	Permissions the agent can change	In the interaction diagram	Defined in the role diagram	None
MaSE	None	Agent to agent interaction modeled as preceding tasks of other agents; no agent–environment interaction	None	None

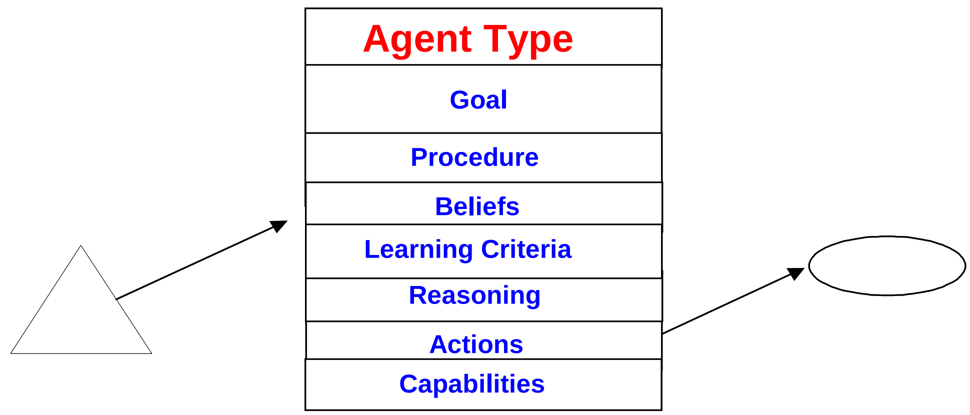

Figure 4. Graphic Representation of an Intelligent Agent

Graphic Representation of an Intelligent Agent-Based System

We now have concepts that fully model intelligent agent behavior. However, writing down all the procedures, beliefs, and goals in a table or in pseudo code form would be cumbersome. This is especially true when modeling the interaction between different types of agents. We propose that a graphical representation of the conceptual framework will aid modelers in designing their agent systems.

Individuals make sense of information by using map-like structures of cognition (Lakoff 1987). By *map*, we mean a "graphic representation that provides a frame of reference" (Foil and Hoff 1992, p. 267). Figure 4 shows the components included in defining an agent using our proposed graphic representation.

All of the concepts in Figure 4 are derived from the previous section with the exception of *Type*, which can be described as the name of a class of agents. A type has its own unique goals, procedures, beliefs, reasoning, actions, and capabilities. An agent has the ability to autonomously change into other types of agents by interacting with the environment.

We also introduce the idea of learning criteria, which shows how the agent "labels" stimuli from the environment. According to Angulin (1992), labeled examples are specific stimuli from the environment and can be positive (sunny = warm) or negative (cloudy ≠ warm) examples of a concept. The learning criteria give the user the ability to set when an example can be labeled as positive or negative.

Perceptions and resources in the model are displayed as either agent or system variables. System variables are properties that make up the state of the world and are shown in the proposed framework as ovals, while agent variables refer to agent properties that are not part of its effector or simulator and are shown in the framework as triangles. In the representation, the difference between resources and perceptions is shown by the agent's relation to the variables. If an interaction arrow goes from the variable to the agent, then it is a perception. However, if the interaction arrow goes from an agent to a variable, then the variable is a resource.

Suppose a researcher wanted to see how a customer responded to various sales and price information and wanted to build an agent-based simulation to investigate this behavior. Figure 5 is an example of how the researcher would model her customer agent using the representation.

In Figure 5, the agent learns which prices, designs, brand names, and features can lead to a high quality computer. It then looks at those variables in the "current" laptop to decide on an expected quality of the laptop.

Along with the distinction between agent and system variables, there are also distinctions between specific and aggregate variables. The customer takes into account store prices of **all** retailers ([PR]) to make a decision about the expected laptop quality. Ownership of a variable is denoted by a subscript. For example, BC_t is the brand name of computer "t".

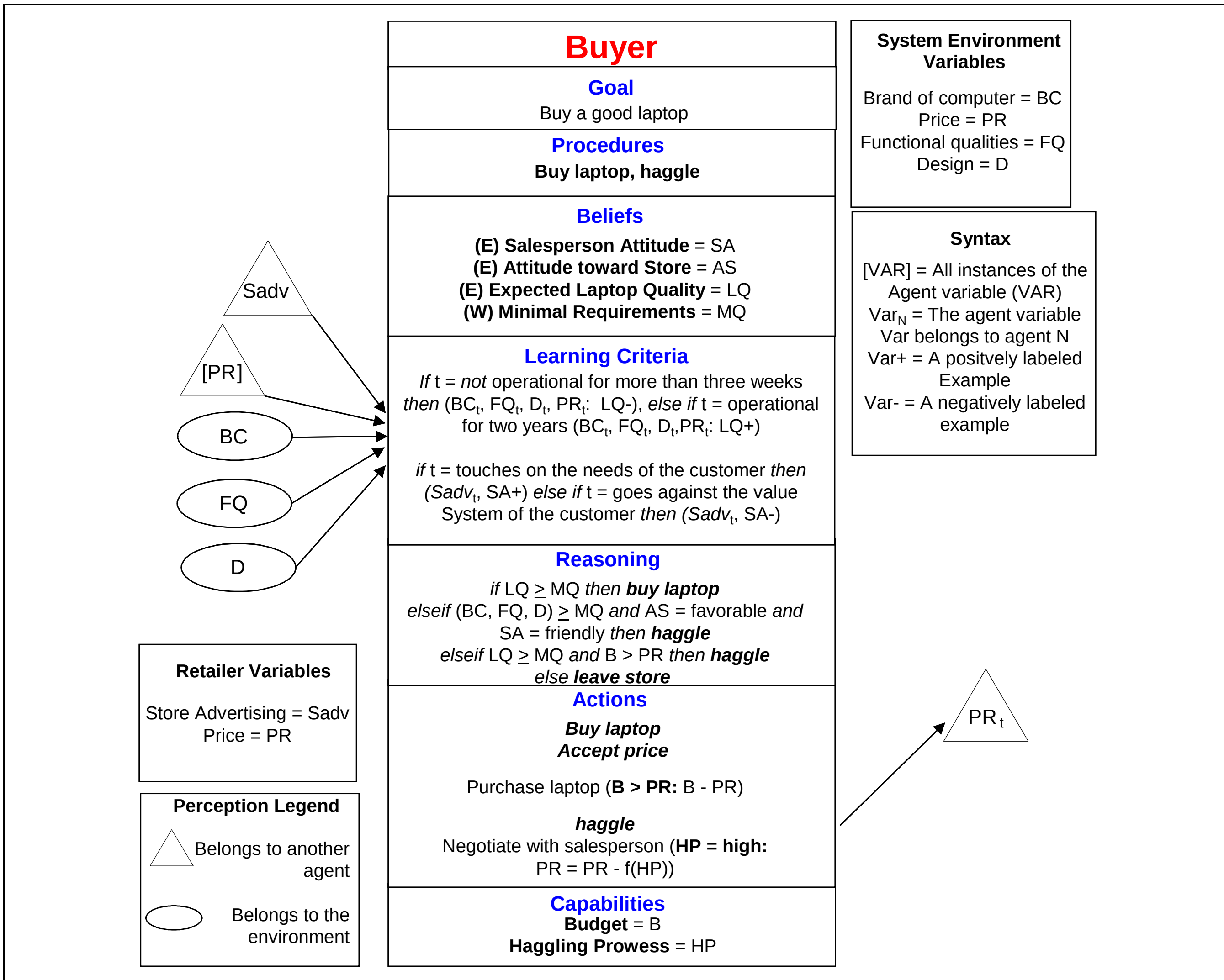

Figure 5. Buyer Modeled as an Intelligent Agent

Another important aspect of modeling intelligent agents is the use of subtypes and transitions. According to Wooldridge (2002), intelligent software agents are adaptable computer systems, therefore it should be possible for them to change type. Sub-types are also useful for modeling purposes because information is not repeated needlessly in the diagram.

A dotted arrow shows that the agent has a subtype. These subtypes have everything that their parent types have but differ specifically with what is outlined in the model.

Now that we have graphical constructs with which to build our models, they must be tested to ensure that they can correctly define a specific problem domain. To do this, we have enlisted the help of marketing researchers and looked specifically at the area of competitive pricing strategy in markets.

Application of the Model: Competitive Pricing Strategy

One possible area of applying agent based modeling is economics and marketing. However many of the computational agents used in the area of economics are very simple (Tesfatsion 2002). One specific application for intelligent agents is competitive pricing strategy research. In this area, firms do not simply react but must also engage in strategic thinking.

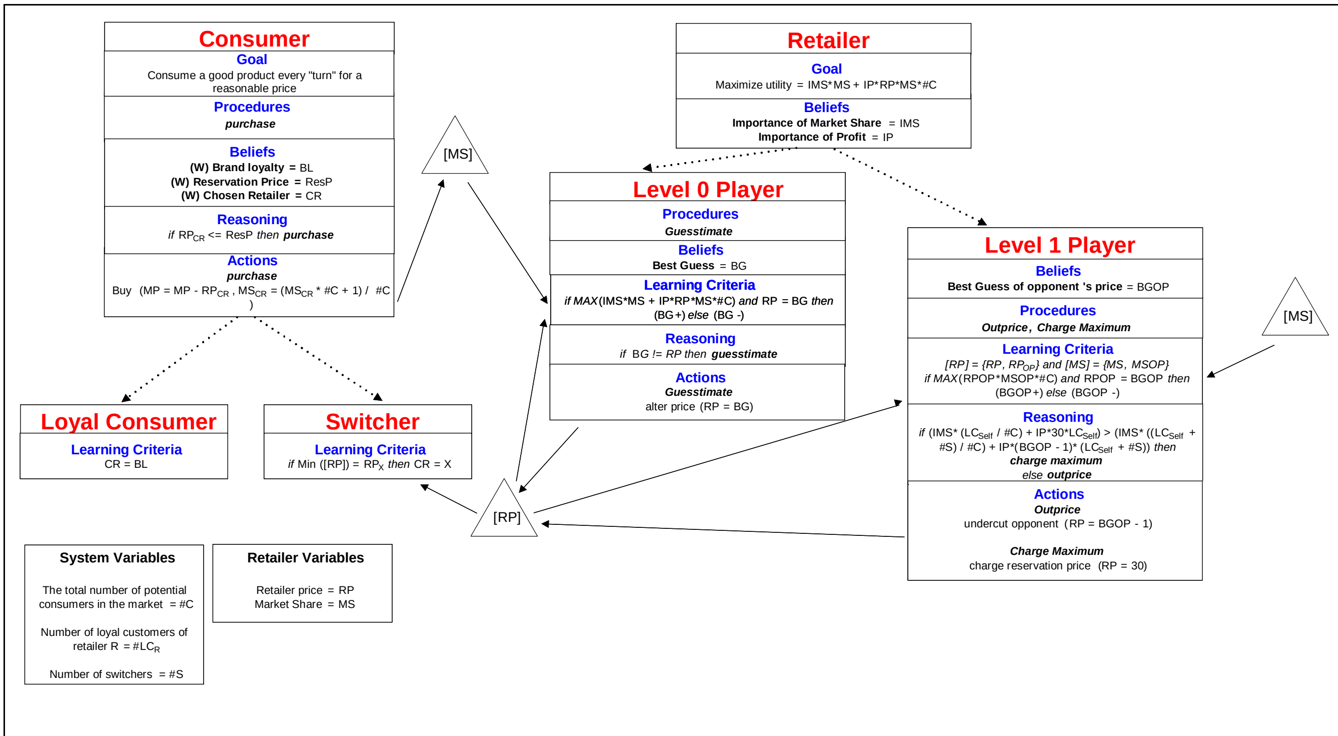

Figure 6. Narasimhan's Pricing Game Modeled as Intelligent Agents

Narasimhan (1988) proposed a scenario for competitive pricing strategy. In this scenario, two firms set a promotional price for a product. Each brand has a loyal segment and there is also a "switcher" segment that will buy whichever brand is least expensive. In this game, players must lower the price enough to attract a large market share but also must make a profit. The game theoretical model of the scenario showed that a Nash equilibrium would be a mixed strategy. In game theory, mixed strategy means that some actions of the players are randomly chosen from a set distribution of values (Reny and Robson 2004).

Choi and Messinger (2004) conducted experiments with human subjects to determine if individuals would randomize their behavior. Their results showed that people sometimes randomized and sometimes followed a cyclical pattern. The question was how this could occur in the same game. Using the information provided by Narasimhan's analytical paper and Choi and Messinger's empirical studies, an agent-based representation of the problem was developed (Figure 6).

In the model, two main agents, retailers and consumers, interact through the variable RP, retailer price. Consumers come in two subtypes, loyal consumer and switcher. Retailers also come in two subtypes, Level 0 and Level 1 players. Level 0 players only use their "personal" past experience to learn how to win the game, while Level 1 players incorporate their opponents' actions into their thinking (Vidal and Durfee 1996). A retailer tries to set prices in a way that maximizes its utility (a mixture of revenue and market share).

Implementation

The model was implemented in an agent-based programming environment called Netlogo (Tisue and Wilensky 2004), which is very amenable to the representation.

Due to Netlogo's lack of statistical analysis tools, the system was also implemented in a statistical programming platform called R (Francisco and Spyros 1999). This was done by the marketing researcher with whom we worked. Even though he did not have previous knowledge of agents, the representation gave him the conceptual tools to build the system in his "own language."

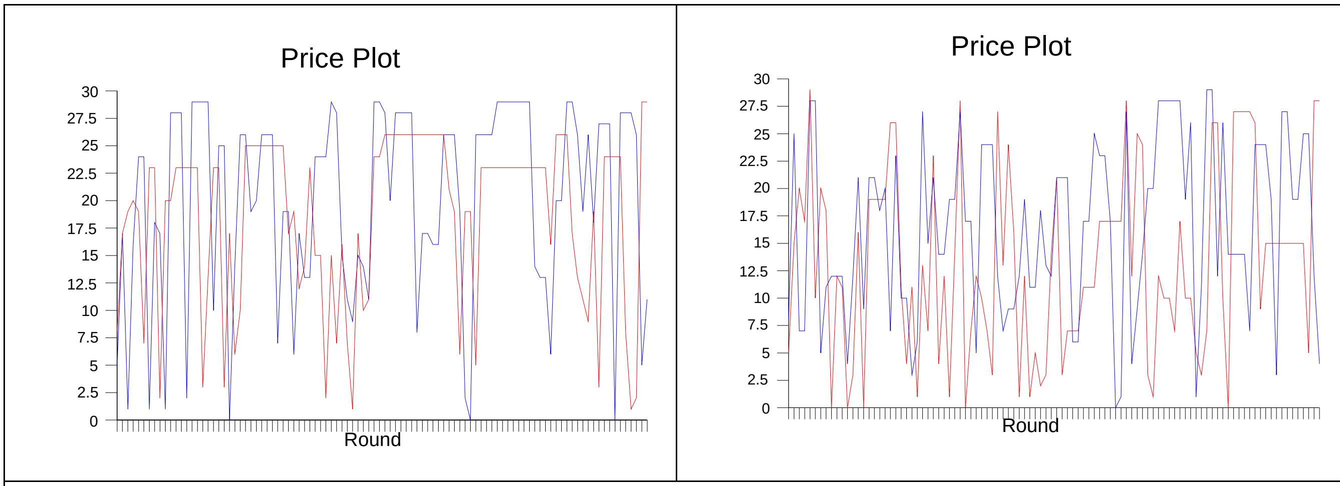

Figure 7. Pricing Graphs for Level 0 Agents: Netlogo (Left: Profit; Right: Market Share)

Results from the Simulation

The reason for creating the simulation was to find the conditions for when partial cycle pricing behavior occurred. To do this, we had to run the simulation in various configurations.

We tested our first hypothesis, which was that agents who cared more about market share would be more likely to engage in cycle pricing behavior. Also, we believed that the different strategy levels would have an effect on pricing, however, we were not sure what it would be. We first tested strategy Level 0 players competing against each other, but we ran two simulations, one where the agents' goal function was weighted toward profit and the other with the function weighted toward market share.

In both simulations the agents seem to randomly set prices, and stay at the same price for extended periods of time. Therefore, our hypothesis that agents who care about market share will try to chase the switcher market using cycle pricing was false. To see if strategy levels would change pricing behavior, we ran two simulations with strategy Level 1 retailers, again varying the weighting of market share and profit in the agents' goal functions.

In these simulations, agents did engage in cycling behavior, entering into price wars, no matter what the weightings of their goal functions. To engage in a price war, the retailers must be trying to model each other's actions. We have compared our data to that of Choi and Messinger and found that patterns in Figure 8 occur in some of their records.

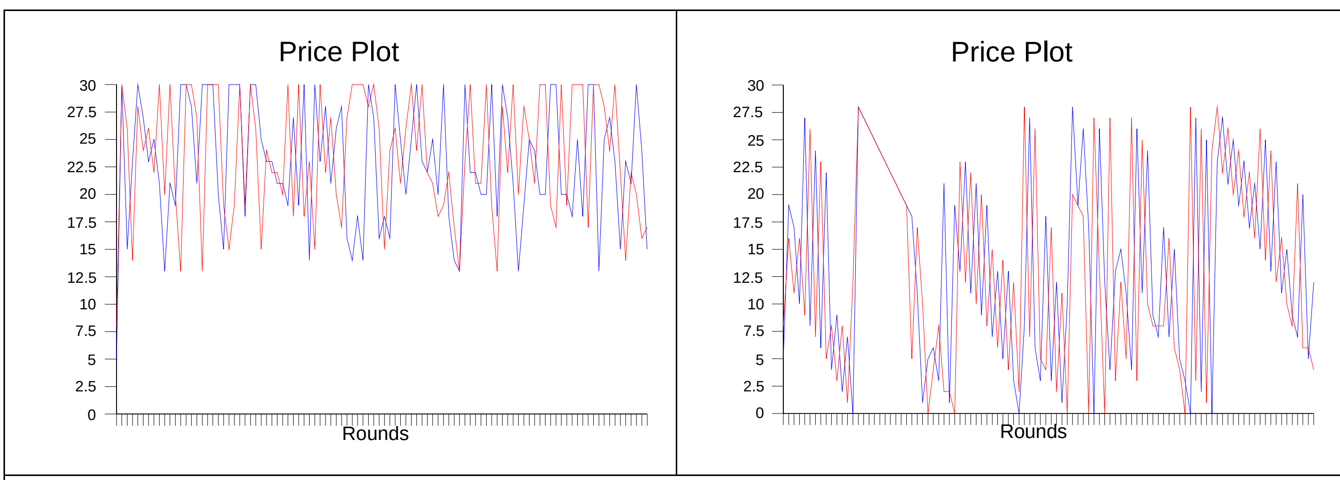

Figure 8. Pricing Graphs for Level 1 Agents: Netlogo (Left: Profit; Right: Market Share)

Conclusion and Future Research

The study began by asking how intelligent agents could be used to model the complex situations in social science. We decided a conceptual model of intelligent agents was needed to aid researchers to communicate and compare their models. In our investigation, we identified the components of an intelligent agent using systems theory and the BWW ontology. These methods guided us through the process of analyzing the components of the intelligent agent system. We then showed that current agent methodologies do not fully model all of the aspects of intelligent agents.

We also provided a graphic representation of this conceptual model and then tested it by developing a multi-agent simulation to solve a marketing problem. The test proved successful and not only did the simulation provide some surprising early results, but the graphic representation was able to guide the marketing researcher in implementing the simulation on agent-based and object-oriented platforms. Therefore, we propose that our intelligent agent framework can be used to graphically model complex phenomena in the social sciences. The other contributions of this study are formally defined and theoretically grounded agent concepts and a definition of the interrelationships between these concepts and the intelligent agent itself.

As more nontechnical users start to see the value of agent-based modeling, more sophisticated tools, like agent conceptual modeling, are needed to aid in the creation of these systems.

However, the current study does have some limitations. Only one problem in one research area was modeled. This might not suffice to show that the conceptual model is applicable to a wide range of situations. Also, the conceptualization of intelligent agents was tested by creating an agent-based simulation, but agents can also be used to perform tasks in the real world (Wooldridge 2002). We have not tested the usefulness of our models to support such applications.

One possible future research direction could be the development of a modeling/programming environment based on the conceptual framework. With such an environment, nontechnical users could automatically create multi-agent based simulations using the graphic representation.

Acknowledgments

The authors would like to thank the anonymous associate editor and reviewers of the ICIS 2005 track, Alternative Approaches to System Development. Their insightful comments greatly enhanced the work. The authors would also like to thank the Natural Science and Engineering Research Council (NSERC) of Canada for their financial support of this project.

References

Ackoff, R. L. "Towards a System of Systems Concepts," *Management Science* (17:11), 1971, pp. 661-671.

Angulin, D. "Computational Learning Theory: Survey and Selected Bibliography," in *Proceedings of the 24th Annual ACM Symposium on Theory of Computing*, N. Alon (Ed.), Victoria, BC, Canada, May 4-6, 1992, pp. 351-369.

Arazy, O., and Woo, C. C. "Analysis and Design of Agent-Oriented Information Systems," *The Knowledge Engineering Review* (17:3), 2002, pp. 215-260.

Bunge, M. *Treatise on Basic Philosophy, Vol 3, Ontology I: The Furniture of the World*, Reidel, Boston, MA, 1977.

Bunge, M. *Treatise on Basic Philosophy, Vol. 4, Ontology II: A World of Systems*, Reidel, Boston, MA. 1979.

Choi, S., and Messinger, P. R. "Edgeworth Cycles and Fairness in Competitive Promotional Strategies: An Experimental Study of Mixed Strategy Pricing," Working Paper, 2004.

Churchman, C. W. *The Systems Approach*, Dell Publishing, New York, 1979.

Drogoul, A., Vanbergue, D., and Meurisse, T. "Multi-Agent Based Simulation: Where Are The Agents?," in *Proceedings of Multi-Agent Based Simulation Conference*, J. S. Sichman, F. Bousquet, and P. Davidsson (Eds.), Bologna, Italy, July 15, 2002, pp. 1-15.

Foil, C. M., and Huff, A. S. "Maps for Managers: Where Are We? Where Do We Go from Here?," *Journal of Management Studies* (29:3), 1992, pp. 267-285.

Francisco, C., and Spyros, G. Z. "R: Yet Another Econometric Programming Environment," *Journal of Applied Econometrics* (14), 1999, pp. 319-329.

Giunchiglia F., Mylopoulos J., and Perini A. "The Tropos Software Development Methodology: Processes, Models and Diagrams," in *Proceedings of the 1st International Joint Conference on Autonomous Agents and Multiagent Systems*: Part 1, C. Castelfranchi and W. L. Johnson (Eds.), Bologna, Italy, July 15-19, 2002, pp. 35-36.

Holbrook, M. B. "Adventures in Complexity: An Essay on Dynamic Open Complex Adaptive Systems, Butterfly Effects, Self-Organizing Order, Coevolution, the Ecological Perspective, Fitness Landscapes, Market Spaces, Emergent Beauty at the Edge of Chaos, and All That Jazz," *Academy of Marketing Science Review* (6), 2003 (available online at **http://www.amsreview.org/articles/holbrook06-2003.pdf**.

Juan, T., Pearce, A., and Sterling, L. "ROADMAP: Extending the Gaia Methodology for Complex Open Systems," in *Proceedings of the 1st International Joint Conference on Autonomous Agents and Multiagent Systems*, C. Castelfranchi and W. L. Johnson (Eds.), Bologna, Italy, July 15-19, 2002, pp. 3-10.

Kim, B., Graves, R. J., Heragu, S. S., and St. Onge, A. "Intelligent Agent Modeling of an Industrial Warehousing Problem," *IIE Transactions* (34:7), 2002, pp. 601-612.

Kirman, A. P., and Vriend, N. J. "An ACE Model of Price Dispersion and Loyalty," *Journal of Economic Dynamics and Control* (25), 2001, pp. 459-502.

Lakoff, G. "Cognitive Models and Prototype Theory," in *Concepts and Conceptual Development: Ecological and Intellectual Factors in Categorization*, U. Neisser (Ed.), Cambridge University Press, New York, 1987, pp. 63-100.

Langdon, C. S. "Agent-Based Modeling for Simulation of Complex Business Systems," *International Journal of Intelligent Information Technologies* (1:3), 2005, pp. 1-13.

Miller, J. G. *Living Systems*, McGraw-Hill, New York, 1978.

Nadoli, G., and Biegel, J. E. "Intelligent Manufacturing Simulation Tool (IMSAT)," *ACM Transactions on Modeling and Computer Simulation* (3:1), 1993, pp. 42-65.

Narasimhan, C. "Competitive Promotional Strategies," *Journal of Business* (61), 1988, pp. 427-450.

Padgham, L., and Winikoff, M. "Prometheus: A Methodology for Developing Intelligent Agents," in *Proceedings of the 1st International Joint Conference on Autonomous Agents and Multiagent Systems*, C. Castelfranchi and W. L. Johnson (Eds.), Bologna, Italy, July 15-19, 2002, pp. 37-38.

Reny, P. J., and Robson, A. J. "Reinterpreting Mixed Strategy Equilibria: A Unification of the Classical and Bayesian Views," *Games and Economic Behavior* (48:2), 2004, pp. 355-384.

Shehory, O., and Sturm, A. "Evaluation of Modeling Techniques for Agent-Based Systems," in *Proceedings of the 5th International Conference on Autonomous Agents*, J. Whatley and M. Beer (Eds.), Montreal, Canada, May 25-June 1, 2001, pp. 624-631.

Sikora, R., and Shaw, M. J. "A Multi-Agent Framework for the Coordination and Integration of Information Systems," *Management Science* (44:11), 1998, pp. 65-78.

Tesfatsion, L. "Agent Based Computational Economics: A Constructive Approach to Economic Theory," in *Handbook of Computational Economics*, K. L. Judd and L. Tesfatsion (Eds.), North-Holland, Amsterdam, 2005 (forthcoming) (available online at **http://www.econ.iastate.edu/tesfatsi/hbintlt.pdf**).

Tesfatsion, L. "Agent-Based Computational Economics: Growing Economies from the Bottom Up," *Artificial Life* (8:1), 2002, pp. 55-82.

Terna, P. "Economic Simulations in Swarm: Agent-Based Modeling and Object-Oriented Programming—by Benedikt Stefansson and Francesco Luna: A Review and Some Comments about 'Agent Based Modeling,'" *The Electronic Journal of Evolutionary Modeling and Economic Dynamics*, Article 1013, 2002 (available online at **http://www.e-jemed.org/1013/index.php**; accessed August 26, 2005).

Tisue, S., and Wilensky, U. "NetLogo: Design and Implementation of a Multi-Agent Modeling Environment," in *Proceedings of Agent 2004 Conference on Social Dynamics*, M. Clemmons (Ed.), Chicago, IL, October 4-6, 2004, pp. 161-184.

van der Zee, D. J., and van der Vorst, J. G. A. J. "A Modeling Framework for Supply Chain Simulation: Opportunities for Improved Decision Making," *Decision Sciences* (36:1), 2005, pp. 65-95.

Vidal, J. M., and Durfee, E. H. "The Impact of Nested Agent Models in an Information Economy," in *Proceedings of the 2nd International Conference on Multiagent Systems*, M. Tokoro (Ed.), Kyoto, Japan, December 10-13, 1996, pp. 377-384.

Von Bertalanffy, L. *General Systems Theory: Foundations, Development, Applications*, George Braziller, New York, 1968.

Wand Y., and Weber, R. "An Ontological Model of an Information System," *IEEE Transactions on Software Engineering* (16), 1990, pp. 1282-1292.

Wand, Y., and Weber, R. "On the Deep Structure of Information Systems," *Information Systems Journal* (5), 1995, pp. 203-223.

Wooldridge, M. *Introduction to Multi-Agent Systems*, John Wiley and Sons Limited, Chichester, England, 2002.