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The Impact of Relational Model Bases on Organizational Decision Making: Cases in E-Commerce and Ecological Economics

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THE IMPACT OF RELATIONAL MODEL BASES ON ORGANIZATIONAL DECISION MAKING: CASES IN E-COMMERCE AND ECOLOGICAL ECONOMICS

A Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University.

by

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And with that, I say, Good night and good luck!

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List of Acronyms

CRM: customer relationship management
DSS: decision support system
DT: decision technology
BPM: business performance management
IPA: intelligent process automation
ERP: enterprise resource planning
OLAP: online analytical processing
SCM: supply chain management
BI: business intelligence

Notation

c: a categorical connective
C: a set of categorical connectives
C': a first-order categorical connective relational operator
d: a decision instance
D: a set of decision requirements
e: an organizational entity
E: a collection of organizational entities
f: a computational expression for coefficient specification
F: a set of computational operations over members of a set of decision factors in pursuit
F': a first-order connective (computational) function
F'': a second-order connective (computational) function
H': a first-order vertical integrative connector
H'': a second-order vertical integrative connector
H''': a third-order vertical integrative connector
k: a task to be performed by an organizational entity
K: a collection of tasks to be performed related to a set of decision requirements
L': a first-order lateral integrative connector
L'': a second-order lateral integrative connector
L''': a third-order lateral integrative connector
N: an integral managerial requirement (within an organizational unit)
O: an organization
p: an instance in an array of decision requirements of some outcome objective
r: an elementary relational operator
R: a primary superior relational operator, conjoining two or more elementary relational operators
$\check{R}$: a collection of higher order relational operators
R': a first-order relational operator
R'': a second-order relational operator

R''': a third-order relational operator
R_o''': a third-order relational operator conjoining all of the tasks an organization includes
U: an organizational unit
υ: current parameter value for indicated variable
v: an instance of a variable in set V
V: a set of decision factors thought to have some bearing on a decision
$\rightarrow$: indicates a mapping
Δ: a change in
$\lrcorner$: absorbed by or expressed within
$\cup$: union
$\subset$: is a proper subset of
$\supset$: subsume
$+$: is superimposed on
$\leftrightarrow$: is equivalent to
$\cap$: intersect
$\forall$: for all

Equivalences

$V_x = \{V \mid d_x\}$
$R(V_x) = R_x$
$r_x(v_m \cap v_n) = r_x(v_m, v_n)$.

Abstract

THE IMPACT OF RELATIONAL MODEL BASES ON ORGANIZATIONAL DECISION MAKING: CASES IN E-COMMERCE AND ECOLOGICAL ECONOMICS

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This dissertation explores reifying the management science concept of organizations as a collection of decisions. Organizational management entails resource allocation activities that can be formulated in terms of elementary relational functions. All elasticity-type formulations, most generic "production" functions, and various projection models that organizations might require (such as sales forecasts) can all be represented by elementary relational functions. Therefore, information systems in organizations can be representative of relationships between decision requirements, as theorized in relational

model bases. A relational model-base structure acts as an integrative device by relating an organization's elementary relational functions to each other, with all that is kept for any model being the current values for coefficients and the now prevailing parametric values for the state variables of the model.

Anchoring management information systems around relational model bases is particularly appropriate for organizations that have some reliance on real-time management decision making by providing the answer to two requirements for such organizations: one being the requirement for more accurate and current real-time, operational decision making within the organization; the other being the integration of functions for decision-making purposes within an organization. Relational model bases thus enable more dynamic management and become a central information system type for organizations that have dynamic resource allocation requirements that can employ technical tactics around such relational model bases. The relational model base would reflect revealed needs in an organization as opposed to projected needs, easing an organization's reliance on forecasting and moving it toward real-time decision making. The case for the introduction of these information systems is further strengthened by the fact that relational model base-type structures are already operating in production environments within organizations.

The methodology used in this dissertation involved modeling organizational decision requirements in particular organizational cases to determine the behavior of relational model bases within those prototypical organizations and the application of relational model bases to real-time decision making. The first organizational scenario is a recursive agribusiness e-commerce case, with the target application being precision agriculture. The second scenario is a non-recursive ecological economics case, with the target application being preservation of biodiversity through land (habitat) protection.

CHAPTER 1 Introduction

Whether talking about organizational decision making within an organization or among organizations, there is a noticeable gap in the literature relating to decision technology. Information systems research focuses largely on the communications processes between human entities that information technology enables, both processes to make an organization more efficient and processes which must happen to support virtual corporations, and the management implications of these communication technologies (such as email, intranets, extranets, etc.). Meanwhile, technical research focuses on the associated technologies that permit the transformation of data into information through decision support. This research encompasses the technical aspects of powerful decision support tools, such as data warehouses, online analytical processing (OLAP), data mining, and Web-based decision support systems (DSS), and the technologies that allow for individuals and groups to transform data into information once the data has been stored (Shim et al., 2002). The gap exists in research on tools that would allow for the synthesis of data prior to processing into a warehouse for decision makers, either solitary decision makers or groups charged with making a decision. Whether it is the lack of technical decision technologies to support virtual corporations (an inter-organizational decision technology deficit) or the difficulty of acquiring quality, real-time, decision-making information within organizations (an intra-organizational decision technology deficit), it is clear that work to improve organizational decision making technically would be a contribution. This dissertation would attempt to begin to bridge that gap by introducing a technical solution (relational model-base structures) for operational and tactical level, real-time, integrative decision making from data prior to its storage in a repository and explicating that solution in two case studies.

This dissertation will explore reifying the management science concept of organizations as a collection of decisions (as opposed to the more familiar management theory view of organizations as collections of people.) The question to be addressed is what is the behavior of relational model-base structures as proposed within prototypical organizations, focusing on how the relational model-base structure acts to integrate organizational functions in real time for decision-making purposes. Additionally, based on this behavior, what is the application of relational model-base structures to real-time decision making is also investigated, focusing on how relational model-base structures facilitate more accurate, real-time decision making within and among organizations. The methodology used in this dissertation is logical modeling of organizations in two specific cases to investigate the behavior of relational model-base structures within those two organizational settings and the application of relational model-base structures to real-time decision making within those organizations.

Two specific organizational cases will be explicated, one in the setting of agri-business and the other in the setting of ecological economics. The first organizational case will focus on decision making within an agricultural supply chain, where the decision functions are driven (or constrained in operation) by one particular recursive demand function, making the decision process hierarchical in nature. In this situation, the relationship between a grain miller and a grain producer is used, where the decision functions are constrained by the amount of grain the miller wants to buy from the producer. The second organizational case will focus on inter-organizational decision making among participants in ecological economics, where there is no one particular demand function that drives the relationship among entities over the other demand functions, where resource allocation is dynamic and more non-hierarchical in nature.

The significance of this research lies in the investigation of several different aspects of decision technology and its effects on organizational decision making. First, it is important to show how organizations would benefit in their decision-making processes by having enhanced real-time information as the result of more tightly integrated decision-making entities within their organization. Second, it is crucial to show how these benefits from enhanced real-time information are salient not just within organizations, but also among organizations. With this real-time information from tightly integrated decision entities among organizations being central to the success of external supply chains and networks and to the existence of virtual corporations (Davidow & Malone, 1992), it is crucial to show these benefits of real-time information among organizations as well. Although the successful application of relational model-base structures could be achieved in many sectors, as the successful application of databases has been achieved in many sectors, the cases presented focus on the agricultural industry and ecological economics in particular, sectors where improved decision making within and among organizations deeply affects people and resources worldwide.

In terms of the real-time aspects of relational model-base structures, these structures provide the technical capability for organizations to make themselves more responsive to competitive conditions as they are occurring, thereby making these organizations more agile and adaptive. Organizations, real or virtual, which choose to operate under relational model-base conventions can expect to reduce their dependency on forecasts in favor of actual current operating conditions, reducing the level of projective risk to which the organizations are exposed. Yet, as a decision technology based on information technology, relational model-base structures have a more specific technical directive, which is to enable more extensive application of relational model-base structures in dynamic resource allocation through their capability of eliciting inputs from real-time data capturing devices, such as ground soil sensors and weather tracking satellites, and transforming those inputs into coherent sets of decision predicates (items of a variety of origins and orders that can inform decision choices).

As integrative instruments, relational model-base structures are designed to aid organizations in realizing higher levels of lateral integration. Higher levels of lateral integration mean more constructive interconnectedness among the activities in which an organization's components (e.g. departments, divisions, etc.) are engaged, or organizations themselves are engaged in the case of inter-organizational associations. Tighter integration should translate into improved organizational performance in terms of input-output ratios (leverages), yield-type measures (e.g. profitability) or any of a variety of other return-related performance criteria. Higher levels of lateral integration imply tighter-coupling, and more tightly-coupled systems can be expected to have higher potential aggregate efficiency than their more loosely-coupled counterparts (Perrow, 1999; Sutherland, 1998). Relational model-base structures can elevate levels of lateral integration by prompting more codeterminancy among decisions in the hopes that the decision choices of each organizational component can be made with more adequate and appropriate consideration of the best interests of the organization as a whole.

While the real-time and integrative capabilities of relational model-base structures are essential to their significance, that relational model bases can be successfully applied in scenarios where decision models must be functionally interconnected makes their investigation even more compelling. Within organizations, enterprise information systems have provided organizations with essential information to integrate different parts of the organization for decision making purposes. However, as many competitive situations require real-time, actionable information much more rapidly and in much greater quantity than ever before, the necessary expansion of the current systems' capabilities is sufficient impetus to investigate potential alternatives in providing such information, as relational model-base structures are theorized to do. Companies must integrate decision making better by attacking within their enterprise "those dark holes, those seemingly unreachable places, obscuring and hiding the information and knowledge that allow them to operate more intelligently and more rapidly." (B. Evans, 2005b) From the standpoint of competitive advantage, enhancing real-time and integrative capabilities becomes even more critical when looked at from the idea of "availability to sale," where a company's advantage is based on finding what their best suppliers are selling as inexpensive inputs and figuring out what can be built with that, while simultaneously investigating if there is enough demand for that product made from the inexpensive inputs to go ahead with the purchase of the opportunistically inexpensive inputs. If the market demand inquiries show enough demand for the product, then the company can buy the inputs that today are very inexpensive and begin to make product that is either better or cheaper than what any competitor can offer, although that product was not on the original forecasted production schedule. An organization's ability to capture and analyze information faster and more fluidly than anyone else continues to be an enormous competitive advantage because it gives companies the power to model themselves in the image of immediate market demand. (B. Evans, 2005a)

If improved real-time, decision-making information through more tightly integrated entities with decision authority provides competitive advantage in an intra-organizational context, then it becomes essential in the functioning of virtual corporations, which are networked organizations linked by information technology to share skills, costs, and access to one another's markets. Changing corporate dynamics, such as outsourcing and downsizing, are transforming many large, multinational corporations into examples of virtual corporations, where non-essential divisions are spun off into separate entities, yet continue to participate along the value chain of the former parent. In this scenario, many organizations can change partners in their value chain and execution strategies more rapidly, providing necessary agility in today's corporate environment. Without improving inter-organizational information technology and decision technology by making the operational data more real-time and more tightly integrating the individual organizations involved in the value chain, organizations with distributed organizational components and far-flung supply networks will struggle to retain the competitive advantage they gain by being virtual corporations in the first place.

This rapid pace of changing corporate dynamics affects all sectors of industry, including agriculture and land development. The agriculture sector is thoroughly global in nature, utilizing advanced information technology and decision technology both within and among industry organizations. There is well explicated and widely published economic and technical data on the global agriculture industry, making it a prime target in developing cases where relational model-base structures might be technically superior to current technical solutions. In the area of agriculture, farmers are widely adopting techniques in precision agriculture, utilizing state-of-the-art sensor and communications technology to maximize profit from crop yields. Increasingly, in making crop distribution and planting decisions, farmers are being called upon to enhance their decision-making processes by considering the impact of more variables in the planting decision process, and being given a shorter amount of time to do so. Farmers might find great utility in relational model-base structures to help them handle the heavy computational requirements of precision planting decisions in the short amount of time in which these decisions have to be made. Therefore, the first case where relational model-base structures will be applied is in a farm site scenario to facilitate precision agriculture. In addition, with their implications for ecology and the environment, as well as their impact on international relations, the importance and wide-ranging implications of decisions made by organizations within the agriculture industry (known as agribusiness) make this industry particularly in need of addressing its decision making judiciously and expeditiously (Greider, 2000).

The second sector that will be investigated is in ecological economics, that of the preservation of biodiversity through land (habitat) protection. This inter-organizational scenario engages several entities with no clear hierarchical relationship among them, making the potential functioning and benefit of a relational model-base structure very interesting. Through this investigation, the economic benefit of the introduction of relational model-base structures into situations that are more non-hierarchical in nature is going to be demonstrated.

The remainder of this dissertation outlines this research in detail. Chapter 2 investigates the enterprise information systems discipline and provides the rationale for relational model-base structures with respect to organizational decision making, while Chapter 3 outlines the theoretical basis for relational model-base structures and the assumptions underlying the application of relational model bases in organizational settings. Chapter 4 will explicate the case of an agricultural entity's execution of precision agriculture, while Chapter 5 will detail an inter-organizational case of preservation of biodiversity through land (habitat) protection. Chapter 6 discusses potential instantiations and implementation of a Type 5 or Type 6 relational model-base structure and analyzes two relational model-base-type systems that are already deployed in production environments in light of the characteristics of an ideal relational model-base structure.

Finally, Chapter 7 concludes this dissertation with a discussion of the research findings and conclusions, in addition to suggestions and possibilities of further research.

CHAPTER 2 Enterprise Information Systems and Discussion of their Implementations within and among Organizations

As background to this research, it is important to discuss the current function and focus of enterprise information systems and what the rationale is for the introduction of relational model-base structures as a type of enterprise information system, both within an organization or across organizations. This chapter will focus on the function of current enterprise information systems within and among organizations and the presentation of the opportunity for relational model-base structures to enhance organizational decision making when applied in an appropriate context by offering significant improvements in decision technology and information technology.

Enterprise Information Systems

Assuming the central organizational management challenge is the rational allocation of resources within an organization, decision technologies are needed to optimize dynamic resource allocation within an organization. In response to the need to react quickly to customer needs and market opportunities, there is an increased interest among management in all organizations in obtaining higher levels of organizational integration among functions and having organizational entities achieve adequate and accurate real-time information acquisition and decision predicates, with emphasis on lateral integration, in pursuit of becoming a fully integrated firm (Balakrishnan, Kumara, & Sundaresan, 1999). A fully integrated firm,

> "is like a spreadsheet in which, when the contents of a single cell are altered, the changes automatically ripple out through the entire organization. Thus, when a customer places an order, all the related operational systems adjust accordingly: inventory, logistics, distribution plans, all the way back up the value chain *(or network)* into manufacturing, scheduling and beyond out to suppliers, so that the necessary parts are ordered. At the same time, the systems of all the lateral functions, R&D, marketing and market research, are informed of the changes, and they, too, 'recalculate' accordingly." (Meiklejohn, 1989)

In the current organizational information technology (IT) operating environment, most organizations use enterprise resource planning (ERP) systems and business intelligence (BI) analysis software, in conjunction with other enterprise systems, such as customer relationship management (CRM) and supply chain management (SCM) software, to provide their real-time, integrated information for decision making within the organization.

The demand for accurate, rapid decision-making capability is impelling today's decision makers to find alternative technologies to aid in their decision optimization quest. Increasingly organizations are becoming more complex, agile and flexible to accommodate rapidly changing competitive factors (Shim et al., 2002). The landscape of corporations involves supply networks and other sophisticated external organizational partner relationships, moving toward the idea of a virtual corporation (Davidow & Malone, 1992). Virtual corporations could be described as the fluid, flexible combination of components of one or more businesses to deliver value to a market (Davenport, 2000). As corporations continue to focus on their core competence (Hamel & Prahalad, 1996), they continue to rely more heavily on partnerships with other functionally specialized companies (e.g. HR specialists, manufacturers) to perform various tasks throughout their organization. These pervasive organizational trends, including globalization, rapid "sense and respond" business models, and corporate realignment, have led to the idea that the 21st century organization will be composed of a series of opportunistic alliances among several specialized organizational entities to address particular market opportunities (Balakrishnan et al., 1999). Snow et. al. (1999) argue that the cellular organizational form, consisting of self-sufficient business entities or cells, is well-suited to achieve local responsiveness while exploiting global efficiency in an environment that demands speed, customization, and ownership.

Whatever the intra-organizational demands for enhanced decision technologies in terms of real-time and integrative capabilities are, the demands are only amplified when discussing inter-organizational situations (Strader, Lin, & Shaw, 1998). Today's enterprise systems do not support the level of agile and secure integration and disaggregation of data and processes required by virtual corporations and value networks (Davenport, 2000) and do not allow for the agility and flexibility required for adaptation to changing business requirements for inter-organizational transaction and process management (Malhotra, 2000). For virtual corporations, the need for real-time information is a necessity, as the ability to predict and quickly react throughout the whole network is a decisive factor of success (Davidow & Malone, 1992). Fast responsiveness from any DSS technology eliminates many of the errors caused by poor forecasting, with time being a valuable resource of a virtual corporation and a commodity it cannot afford to waste. In accommodating the range of possible relationships between entities in a virtual organization, enterprise systems will need to support different levels of data integration and process integration, from simple inter-organizational transactions to complete integration and sharing, that are appropriate for the relationship between the two (or more) organizations that make up the virtual organization (Davenport, 2000).

Most organizations, even today, operate as functional islands using tactically-oriented information systems (Wigand, Picot, & Reichwald, 1997). Vendor management systems automate the procurement of indirect resources, while extended supply chain management includes collaborative forecasting and planning, scheduling and logistics (Fingar, 2000). To support greater inter-organizational coordination and virtual corporations, enterprise information systems will have to evolve, retargeting internal systems outward. Using Balakrishnan et al.'s (1999) framework, enterprise systems are already evolving along four dimensions, with one of the dimensions being enterprise integration spanning organizational boundaries. Within this enterprise integration, a primary capability must be to provide more real-time information for decision making. Although current tools support some of the required functionalities, more sophisticated versions of the IT applications are now possible and needed. The continued challenge remains to ensure the agility and adaptability of information, both internally and externally, required to handle dynamically changing business and competitive environments (Malhotra, 2000).

Business value is what drives the development of enterprise systems, and by looking at the potential for creating value, one can map out areas of probable development for the technological aspects of enterprise systems. As most companies that have implemented an enterprise system have done so with a focus on technical value, the same focus is likely to continue into the near future (Davenport, 2000). Hence the timeliness of an alternative technology designed to provide enhanced tactical value to enterprises.

Introduction to Relational Model-Base Structures

In the quest to provide enhanced real-time and integrated information to organizational decision makers, a fundamental change has taken place with respect to how decision predicates and enterprise information are processed in decision making. One of the central themes of modern organizational administrative practice is the incorporation of decision models encoded for computer execution, such as decision agents and intelligent systems, operating as managers charged with basic managerial tasks, including resource allocation tasks. No longer can information systems merely provide basic decision predicates to the decision makers and be effective; instead, these decision predicates need to be input directly into information systems containing model bases to process the data, thereby providing actionable information to the organizational decision makers. This is the movement of information systems in organizations in general, as many competitive situations now require actionable information much more rapidly than ever before, minimizing lengthy (or impossibly complex) manual analysis or storing and subsequently retrieving and processing the data from relational databases.

While many of these decision agents have been used in a capacity as passive decision aids to a manager, some decision agents have been configured to function as active decision models that can be invested with decision-making authority over certain tasks, moving from the realm of business intelligence to functioning as artificial intelligence. The tasks most likely to be addressed by active decision models will be those for which human managers are ill-suited, i.e. tasks with heavy computational requirements and strict timeliness or response-related requirements. Though not all organizations will entail such tasks in any appreciable manner, there are reasons to expect that more organizations will become more heavily dependent on active decision models as time goes along.

As these decision models assume more wide-ranging functionality, it follows that there will be an increased emphasis on enabling functional interconnections (dependency, codeterminacy, etc.) among decision models, analogous to arranging for interactions among human managers. In situations where there is greater autonomic computer management functionality, the need for these functional interconnections among decision models will be even more critical for the decision-making capability of the computer models in their managerial tasks. This prospect poses that some organizations will find themselves in need of a fundamentally new class of decision support facilities that can effectively integrate two or more decision models. These might then be employed in addition to communication-type tools (interactive conferencing techniques, groupware, and data-sharing networks) that have evolved to expedite interchanges among decision makers. Several competitive scenarios demand increased management through decision models, not only for economy, but also for competency in handling such volumes of data expediently and accurately for decision-making purposes. Hence the proposal in this dissertation of one such alternative.

This is the rationale for relational model-base structures, which can provide the technical capability for encouraging constructive interconnections among decision models in the overarching process of providing more adequate and accurate real-time, decision-making information from within a more tightly integrated enterprise. While relational model-base structures might be widely applicable across the organization, the tasks for which relational model-base structures apply exhibit two important characteristics. First, the tasks must involve situations where there are regular decision instances, where the decisions are recurrent and routine. The decision task must also admit to a conventional, technical, algorithm-driven solution where decision choices are deterministic or probabilistic in nature. Therefore, relational model-base structures would be applicable only in scenarios where the decision outcomes are reasonably well-bounded. As mentioned previously, the tasks most likely to be addressed by relational model-base structures are those tasks with heavy computational requirements and strict response-related requirements.

Relational model bases are proposed as an integrative decision device to improve the decision-making capabilities of a firm moving from a forecasting model of production decision making to real-time decision making for technical, tactical, probabilistic production operations decisions. Relational model bases would address transaction automation and process automation with internal, integrated processes, as well as transaction and process automation with inter-organizational (peer) processes. While the development of model-based DSS is still at an early stage, there is now more transparent access to data from across various data warehouses within an organization, making it possible to run models based on actual data (Shim et al., 2002). Cohen et. al. (2001) describe several implementations of optimization-based DSS that integrate data from several sources, signaling model-based DSS as finally poised to emerge as a powerful tool for organizational decision making. A relational model-base structure acts as an integrative device by relating an organization's elementary relational functions to each other.

In addition to the enhanced integrative data capabilities of relational model bases, the capability of relational model bases will also extend to the ability to provide real-time processing of data. While relational databases and data warehouses do provide the necessary repositories for corporate data as the basis of *a posteriori* analysis, anchoring management decision support information systems around relational model bases (perhaps within the context of decision-driven data warehouses) is particularly appropriate for organizations that have some reliance on real-time management decision making. Opting for a real-time approach can contribute to managerial effectiveness by setting up the conditions for dynamic resource allocation and cultivating reactive management by fostering alertness, quickness, agility and resilience in the organization's competitive environment (Davenport, 2004). The relational model base would be a network construct which would reflect revealed vs. projected needs in an organization (for example, dynamic resource allocation in an agribusiness environment), easing an organization's reliance on forecasting and moving it toward real-time data for decision making.

From an economic perspective, the application of relational model bases would increase profit by decreasing operational costs in an organization through the relational model base's ability to provide real-time, more tightly integrated enterprise information. The implementation of any significant new enterprise information system would incur great cost to the organization, both in financial and organizational impact costs. However, despite the substantial fiscal and social impact that the introduction of an relational model-base structure to the organization would have in terms of people and the relational model base's effect on the organization's business processes, the benefit provided by the relational model-base structure in the form of more adequate and accurate decision-making information is conjectured to surpass its cost and ultimately make the firm more profitable.

The case for the introduction of relational model bases is further strengthened by the fact that there already exist cases where decision predicate data goes into models and is processed in real time when response requirements in the situation are high. The decision makers in the organization cannot be reasonably expected to meet the data processing demands that a high response, real-time situation requires; therefore, these decision makers turn to real-time, multi-criteria, multi-decision making tools that can provide this capability. In the case of precision agriculture, the data from many different data acquisition sources must be synthesized to provide the farmer with the information needed to determine the planting variables that result in the optimal harvest outcome. As many of the data acquisition sources are remote sensors and archival predicate databases, the most efficient way to synthesize all of the data sources to effect accurate, rapid decision making is processing data through a relational model-base structure, where the decision outputs can subsequently be provided to organizational decision makers (in this case, the farmers) to determine the values or course of action that would result in the optimal outcome.

An example of a relational model-base-type system already developed and in production in a field where real-time, high response decision-making scenarios exist is the AgLeader Insight Precision Farming System. The Insight System has been developed to provide farmers with the ability to synthesize GPS satellite location data with sensor data on weather and current conditions and historical data about prior planting outcomes through a model base consisting of related decision models in the system. As a result, the farmer has the most current, aggregated information to be able to make decisions on seed type, irrigation, and fertilization of the field plot. Another example of a relational model-base-type system in practice in ecological economics is the Integrated Dynamic Landscape Analysis and Modeling System (IDLAMS). If these types of systems have already been developed in response to naturally occurring problem situations in real-time organizational decision making, it follows to provide a more formal treatment of how these model bases might be constructed and demonstrate how these systems can be applied in practice to similar organizational decision-making situations. These cases can provide guidance for other organizations to introduce relational model-base structures that would be advantageous in the organization's particular competitive situation.

In summary, relational model bases as a type of information system provide an answer to two requirements for organizational information systems informing decisions with high computational and strict response-related requirements. The first requirement is the integration of functions for decision-making purposes to encourage constructive coordination among decisions made by the organization's operational units. The other requirement is more sophisticated real-time, operational decision making in organizations in order to aid the transition to dynamic (vs. forecast-driven) resource allocation decisions. Relational model bases will enable dynamic management and will become central information systems for organizations that have real-time dynamic resource allocation requirements and want to encourage deeper inter-unit decision interrelationships. It is the simultaneous nature of these two missions that determines the constitution and mechanics of relational model bases.

CHAPTER 3 Theoretical Basis of Relational Model Bases

In the forward march of decision support technology, there has been a steady flow of models and tools for multi-criteria decision making in DSS applications. Intelligent logic, which supports tolerance for imprecision, uncertainty, partial truth, and approximation (as opposed to standalone artificial intelligence modules), is now usually inherent in the processing of all decision support tools (Shim et al., 2002). Though information technology is advancing all aspects of decision support, the development of model-based DSS is still at an early stage and finally poised to emerge as a powerful tool for organizational decision making. One of the challenges in employing models for decision support has been the availability of data from across various data warehouses within an organization. The current approach is to have optimization-based DSS that integrate data from several sources into specific interfaces to make these applications possible. However, relational model bases take a radically new approach. Instead of relying on data warehouses, the models are decision driven, with the data being analyzed in real time through these adaptive models. The purpose of this chapter is to describe relational model bases and how they would improve the real-time and integrative properties of enterprise information processing for dynamic resource allocation, a regular organizational decision-making situation.

In determining the worth of any instance of decision technology, the organization must consider that any instance of decision technology is of positive practical value only to the extent that it is able to provide decision makers with more accurate decision predicates and decision choices on which to base their allocation decisions than otherwise presumably would have been the case. The key intent of relational model bases would be to enhance dynamic resource allocation by making probabilistic decisions less probabilistic and more deterministic in nature by integrating decision making across the organization and enhancing real-time enterprise information to the point where the speed of relational model-base data processing with a certain time interval transforms a probabilistic decision into a deterministic one.

The key assumptions underlying the relational model-base structure are that the relational model base can only address situations involving regular decision instances, where the decisions are recurrent and routine in the situation. The decision must also admit to a conventional, technical, algorithm-driven solution where decision choices can be made by mathematical or statistical inference techniques. Therefore, relational model bases would be applicable only in the operational and tactical managerial decision domains, as these are where decision outcomes are reasonably well-bounded. A mature relational model-base structure should contain a relational substructure for each of the regular decision instances an organization includes. As with data warehouses where there is a logical structure above the warehouse that is housed for decisions that are likely to be made, so many of the assumptions of these data warehouses would also be made for relational model bases consisting of regular decision instances. The primary difference between relational model-base analysis and data warehouse analysis is that the relational model-base data processing is done prior to the data being stored in a relational context, while the data warehouse performs the processing after the data is stored, allowing the relational model base to provide more current data as the basis for decision predicates.

The assumptions that limit the applicability of the relational model-base structure indicate its complimentary nature with other organizational decision-making tools, such as relational database systems for *a posteriori* data analysis and other strategic information systems that cover non-routine or irregular decision instances. This suggests that the relational model base can be added as an organizational decision-making tool to these that already exist in the enterprise. Organizations faced with decisions involving high computational requirements needing to be made in real time would benefit from such a decision support system as one based on a relational model-base structure, regardless of the organization's culture or other organizational distinction, considering the decision domains to which relational model bases are applicable. The relational model base can provide more current and accurate real-time information for analysis through enhanced lateral integration of decision-making entities in a technical system within the enterprise.

The basis for relational model-base constructs comes from the management science conception of organizations as assemblages of decisions (March & Simon, 1993; Simon, 1973), as the primary task for a management scientist is the development of decision aids. This view of an organization (O) would allow it to be represented as a simple mapping, O

$\rightarrow$ D x E, where D is a set of decision requirements distributed in some way among a collection of organizational entities, E. This is represented in Table 1:

Table 1: Decision Tasking Table

	Organizational Entities		
Tasks	E_1	E_2	E_m
K_1	$D_{11} = (d_{1,1,1} \ldots d_{1,1,i})$	$D_{12} = (d_{1,2,1} \ldots d_{1,2,i})$	$D_{1m} = (d_{1,m,1} \ldots d_{1,m,i})$
K_2	$D_{21} = (d_{2,1,1} \ldots d_{2,1,i})$	$D_{22} = (d_{2,2,1} \ldots d_{2,2,i})$	$D_{2m} = (d_{2,m,1} \ldots d_{2,m,i})$
K_3	$D_{31} = (d_{3,1,1} \ldots d_{3,1,i})$	$D_{32} = (d_{3,2,1} \ldots d_{3,2,i})$	$D_{3m} = (d_{3,m,1} \ldots d_{3,m,i})$
K_n	$D_{n1} = (d_{n,1,1} \ldots d_{n,1,i})$	$D_{n2} = (d_{n,2,1} \ldots d_{n,2,i})$	$D_{nm} = (d_{n,m,1} \ldots d_{n,m,i})$

The basic entry in a decision tasking table is a singular decision instance. In Table 1, a decision instance appears as some $d_{k,e,p}$, which identifies it as the p^{th} member of the array of decision requirements pertinent to the k^{th} task, consigned to the e^{th} entity. For simplicity, decision instances throughout the rest of this chapter will be fixed with a single subscript, so that $d_{k,e,p}$ becomes d_x. D_{nm} is the list of decision instances undertaken by the m^{th} entity pertaining to the n^{th} task.

From an organizational perspective, the entities (E) heading the columns of the decision tasking table do not need to have any direct correspondence with the formal organizational components that appear in organizational charts; in fact, some disconnect might be desirable (Rogers & Blenko, 2006). Formal organizational components constitute centers of administrative authority, while entities in the decision tasking table represent repositories of decision responsibilities. The term 'entity' covers a wide spectrum of decision agencies and may include conventional line-of-business managers, groups of executives, man-machine complexes, even autonomous computer decision devices. Ordinary organizational representational forms, including organizational charts, tend to have a strong vertical nature. Formal administrative authority is assumed to cluster at the top of the managerial hierarchy and exercised dominantly downward along the chains of reporting, accounting for the recursive character of conventional administratively-centered organizational process models.

Alternatively, given the lateral orientation of relational model-base structures, interactions through processes among organizational entities can be of a reciprocal, or otherwise non-hierarchical, nature. Therefore, understanding interactions among entities will require the development of non-recursive models, such as cellular-connectionist constructs (to be discussed shortly). Allowing the separation of decision-making entities and administrative units precludes the possibility of the prevailing organizational structure being imposed as an existing constraint on the design of a management support system. This provides the opportunity for technical considerations to influence organizational configuration commitments, possibly bringing administrative and technical apparatus within an organization into better alignment through utilizing decision-making entities rather than organizational departments.

As for all tasks, they are amalgams of two or more dependent decision instances. (Implicit in the assumptions of relational model bases is that every definable task has the possible set of decisions involved fully identified.) Any task could then be denoted as $K_j \supset \{d_{k,e,p}\}$ or $\{d_x\}$, meaning that the task is taken to subsume (per $\supset$) the set of decision requirements defined on the right-hand side. Decision instances themselves are higher-order constructs. Each is underlain by a superior function, $F\{V \mid d_x\}$, where V is a set of variables (decision factors) thought to have some bearing on the decision at hand $\{d_x\}$, and

F prescribes a set of computational operations over the members of V in pursuit of some outcome objective (goal, decision criterion). [From here forward, we define $V_x = \{V \mid d_x\}$.] The establishment of F-type functions can transform decision instances from passive descriptive artifices into proper (fully explicated and executable) decision models, requiring all four of the levels shown in Table 2:

Table 2: Specification Requirements for Proper Decision Models

	DIMENSIONS [LEVELS OF ANALYSIS]	NOTATIONALS
Structural	**Determinant:** Defines an array of variables *qua* decision factors [V] which, when large or significant, may be culled to include only a subset of assumedly most significant factors	$\{V \mid \rho(V) > \varepsilon\} \subset V_x$, which restricts membership to factors/variables whose impact/pertinence (ρ) is expected to exceed a minimal acceptance level (ε)
	Connective: Delineates *intra-decision* intersect ($\cap$) conditions via a set of categorical, connective operators, (C), so indicating which decision variables are expectedly linked with which others, in what ways (influence patterns), under what conditions	$\{C \mid d_x\} = \{c(v_m \cap v_n) \mid v_m, v_n \in V_x\}$, where c-type operators define relationships between/among variables in terms of categorical (i.e., qualitative, logical) connectors
Magnitudinal	**Coefficient:** Supplies a computed or imputed measure of the strength/intensity of the various inter-variable connections defined above	Coefficient specifications (f) are most often of the form $v_n = f(v_m) \leftrightarrow f(v_n, v_m)$, with f typically being a computational (algorithmic) function
	Parametric: Assigns point-in-time numerical values (observation and/or function driven) to each of the determinants/decision variables	$\{v_{m,t}\}$, $\forall\, v_m \in V_x$, where $\{v_{m,t}\}$ is a vector containing the current (time-t) values for all decision variables

Assuming that the decision choices are actionable, for a fully explicated decision model to become executable, it needs to be fitted with the criterion/criteria to be used to effect the selection of decision choice or course of action (which, when taken in concert with determinant-level specifications, constitutes a decision calculus.)

It is now possible to introduce the lowest-order relational entry in a relational model-base structure. It is an elementary relational operator (r) that captures the intersect conditions between pairs of decision variables, e.g. $r(v_1:v_2)$ affecting d_x can be decomposed into $v_2 = r(v_1)$ and $v_1 = r(v_2)$. Elementary relational operators thus conjoin (denoted by $\cup$) both connective and coefficient level specifications as $r = c \cup f$, where f is a computational expression, and c is a categorical connective, perhaps drawn from a set like the following (this is not a complete set of relationships, merely a few examples drawn from the set):

if $c(v_1:v_2) =$
- $\uparrow$: v_2 is positively and proportionally related to v_1
- $\Uparrow$: v_2 is more than proportionally positively related to v_1
- $\downarrow$: v_2 is inversely related to (negatively correlated with) v_1
- $\Downarrow$: v_2 is strongly negatively (inversely) related to v_1
- $\Rightarrow$: v_2 is dependent on (dominated by) v_1
- $\Leftarrow$: v_1 is subordinate to v_2
- $\leftrightarrow$: v_1 and v_2 are co-determinate
- $\leftrightarrow$: v_1 and v_2 are symmetrically (reciprocally) interrelated
- Φ : v_1 and v_2 are deliberately to be kept independent, so that $v_1 \cap v_2 = 0$.

Connectives may be compound, e.g., $c(v_m:v_n) = (\Rightarrow \Uparrow)$ would describe a case where causality is both unidirectional and more than proportionally positively related, such that any change in the value of v_m is expected to incur a more than proportional change in v_n in the same direction. A corresponding computational function would then be of the form $f(v_n, v_m) \rightarrow v_n = v_m^2$, so $\Delta v_n / \Delta v_m > 1$. This suggests there will be cases, many in the decision situations dominating the day-to-day decision making of most organizations, where qualitative connections can be expressed in mathematical terms. In such cases, connective conditions will have been enfolded into, or absorbed by (per the symbol $\hookleftarrow$) a computational expression, so that: iff $(f \hookleftarrow c)$ implies $v_n = r(v_m) \equiv v_n = f(v_m)$. That is, whenever a computational expression can be used to cover both connective and coefficient-level specifications, the former can be considered equivalent to, and hence replace, an elementary relational operator. Whenever such an exchange can be made, the practical consequence is an opportunity for a neatly algorithmic, entirely computer-controlled operation, as is the implication of the f-type expressions that command the cells of the sample relational model-base substructure, shown in Table 3 below.

Back to superior functions, any $F(V_x)$ will include as many subordinate (f-level) functions as there are unique, non-null intersects (pairings or otherwise) among the members of the decision variable array, or: $F(V_x) \supset \{f(v_m{:}v_n)\}$ for all $(v_m \cap v_n) \neq 0$. Any superior function will also have a relational correlate as $R(V_x) \rightarrow (r_1 \cap r_2 \cap \ldots \cap r_z)$, where R is a superior relational operator, conjoining two or more elementary relational operators. Just as expressions of elementary relational operators incorporate computational expressions, superior relational operators can incorporate an associated computational superior function, so that $R(V_x)$ ↵ $F(V_x)$. Additionally, just as the connective condition specified in elementary relational operators can be rolled into computational functions, there are also occasions where $R = C \cup F$, so that $R(V_x) \equiv F(V_x)$, where V_x is the set of variables that have an appreciable impact on d_x. [From here forward, we define $R(V_x) = R_x$.]

In any case, it is these superior relational functions that, when deconstructed as in Table 3 below, become the basic building blocks of relational model-base structures.

Table 3: Configuration Features of a Relational Model Base Substructure $R(d_x)$

	υ_1	υ_2	υ_3	υ_m
v_1	ϕv_1	$f(1,2)$	$f(1,3)$	$f(1,m)$
v_2	$f(2,1)$	ϕv_2	$f(2,3)$	$f(2,m)$
v_3	$f(3,1)$	$f(3,2)$	ϕv_3	$f(3,m)$
v_m	$f(m,1)$	$f(m,2)$	$f(m,3)$	ϕv_m

The cells of a relational matrix (excepting those lying along the major diagonal)[1] will contain elementary relational operators (coupling and coefficient specifications) or, where connective conditions can be captured in a computational construct, a computational expression. Values for these computational functions can be observation-based, induced or imputed. For example, r(m,1) is an elementary relational operator covering both the character and magnitude of the actual or anticipated impact of variable v_m on v_1. This relational entry can be replaced by a computational expression, f(m,1), if the categorical connectives covering the nature and direction of the variable's influence can be absorbed by a f-type expression. The υ_m variables contain the current (time t) working value for the variable v_m. When all the cells in a relational substructure contain computational (f-type) expressions, the result is essentially a coefficient matrix. This opens up some obviously interesting possibilities as to the mechanics for interconnecting decision models, say d_x and d_y, when both $F(d_x)$ and $F(d_y)$ generate decision models defined as linear systems of equations.

The primary cells of a relational matrix/substructure are those lying below (to the southwest of) the major diagonal. The secondary cells, those sitting above and to the right of the major diagonal, are of material significance only when there is relational asymmetry, where r(i,j) $\neq$ r(j,i) and f(i,j) $\neq$ f(j,i); otherwise, they can be left empty. The peripheral

[1] As noted in Table 3, the cells lying along the major diagonal are attended by ϕ -type functions that allow for forced values. This is a nod to the possibility that it may sometimes be desirable to directly determine variable values rather than having them remain data-driven. There might, for instance, be enough regularity to anticipate changes in variable values, or perhaps some reason to distrust some segments of a data stream; allowing for forced values also provides an opportunity to perform simulation-like operations over the components of relational model base structures.

cells heading the columns hold current parameter values for the indicated variable, e.g. $\upsilon_m = \upsilon_{m,t}$ is the prevailing point value for $v_m \in V_x$. Cells lying along the major diagonal are ϕ-type functions, which can be used to force values for variables. These functions can be reflexive ($\phi = dv_m/d_t$), conditional ($\phi = \partial v_m, \partial X_j$, where X_j is an exogenous factor), or prescribe a projective (extrapolative) operation. ϕ may also constitute a complex construct, e.g. a regression tree.

At any moment, a relational model-base substructure encodes all that is known, or thought to be known, about a particular decision requirement. Blank cells, other than those deliberately left empty because they are redundant, would indicate those points at which a decision model is incomplete. Areas where existing relational (connective or coefficient-level) specifications are weak or suspect would presumably become high priority targets for additional information acquisition efforts.

Relational Model Base Real Time Operations

Two factors that make the adoption of a more agile managerial approach increasingly possible are the proliferation of real-time, data-capturing devices and continuing improvement in digital conversion and transmission technology. Both advances have done much to decrease the time interval between the emergence of informational items and their availability as decision predicates for decision support applications. The practical impact of this is most apparent for the applications involving the rational allocation of scarce resources.

When faced with the duty of rational allocation, one of the efforts that decision makers would be expected to make would be to exploit opportunities to decrease the dependency of resource disposition decisions on predictive predicates in favor of more recent, actual inputs of more recent vintage. Allocation choices that owe less to expectations and more to actualities should also have a correspondingly better chance of winding up remaining somewhere in the neighborhood of maximal marginal efficiency for whatever efficiency criterion applies. This is the primary motivator for attempting to move allocation decisions towards a more real-time orientation and the rationale behind building case studies involving dynamic resource allocation.

Making decisions 'more dynamic' does not mean that there is no longer any predictive aspect to the decision. What it implies is a shortening of the projection horizon. This brings about significant advantage, as longer range forecasts will necessarily have higher projective error potentials than their nearer term counterparts for any given subject and associated conditions. Assuming a risk-averse stance on the part of an organization, moving an allocation decision towards a more real-time orientation must then necessarily have a beneficial effect, as it implies a transit from longer to shorter range forecasts. The consequence of this should be some reduction in the costs an organization can expect to incur as the result of predictive errors, assuming costs associated with an erroneous forecast will be tied more or less directly to the absolute value of the difference between actual and predicted demand. This can be used on other types of prediction as well, such as input prices, etc. Reducing the time interval between the point at which a decision commitment is required and the period to which it is to apply gives realities more time to reveal themselves, which leads to decisions that are somewhat less probabilistic.

Dynamic Updating of Decision Models

Real-time matters in a relational model-base substructure are set in motion by the appearance of new data items reporting more and the most recent observations that might cause a change in the value of a variable. There are several approaches that can be used to assign point in time values to variables, three of which are going to be discussed here. The first approach is to have variable values derived entirely from direct measurement, with no substantive mediation of the data, resulting in parameter values of which the decision makers can be quite confident. The second approach is to have variable values be the product of statistical conditioning, ranging from the calculations of means and standard deviations to the use of quite elaborate projective functions. These statistical treatments will yield either range estimates or an inferential value whose veracity must itself be treated as a variable.

The third approach has current variable values computed via a procedure similar to that used to provide decision predicates for dynamic programming exercises (DeNardo, 2003). It is this approach that would be adopted for the real-time orientation of relational model-base structures. Data is derived from a sequence of observations on variables of interest and is then taken to represent running samples, with the sampling frequencies set with consideration to the volatility of the subject of interest. Inputs will ideally be sought from multiple sources, with the selection sources respectful of the rules for devising properly random and adequately representative samples. The resultant data could then drive a Bayesian-type updating function, e.g., $\ddot{\upsilon}_{m,t} = \beta(\varsigma \cup I_t)$, where $\ddot{\upsilon}$ is the current (time-t) Bayesian-dominant valuation for v_m, ς is the prior data set (an assemblage of all previously handled historical values for v_m), and I_t is a posterior data set housing the values acquired during the latest iteration of the measurement/observational exercises on v_m.

The advantage of Bayesian-type parameter setting mechanics is that they can be easily tuned and dynamically retuned to allow relatively more recent data to regularly exert relatively more influence. Should it happen that the receipt of new data forces a significant enough change (increase or decrease) in the value of a variable, this would then subsequently induce changes in all the other variables subject to the original variable's influence. The specifics of these changes would be determined by the character of relational operators, or mathematical functions, sitting in any activated cells of the relational substructure in which v_m is embedded. Alternatively, things may be arranged so that a change in a variable's value could induce a change in the value of a coefficient tying it to another variable, or variables, and so propagate from there throughout the relevant portions of a relational substructure. In any event, a change in the value of any component variable or coefficient should trigger a rerunning of the affected decision model, and so possibly to a new decision choice or revised course of action. Beyond this, amendments made to one decision model might resonate outward to effect correlating changes in other decision models. This eventuality requires investigation into relational model-base structures as integrative devices.

Relational Model Base Integrative Requirements

In turning to the integrative requirements of relational model-base structures, it is useful to begin with the conventional view of an organization as a collection of ordinary organizational units, $O \supset \{U_1, U_2, \ldots U_z\}$, as shown in Figure 1 below.

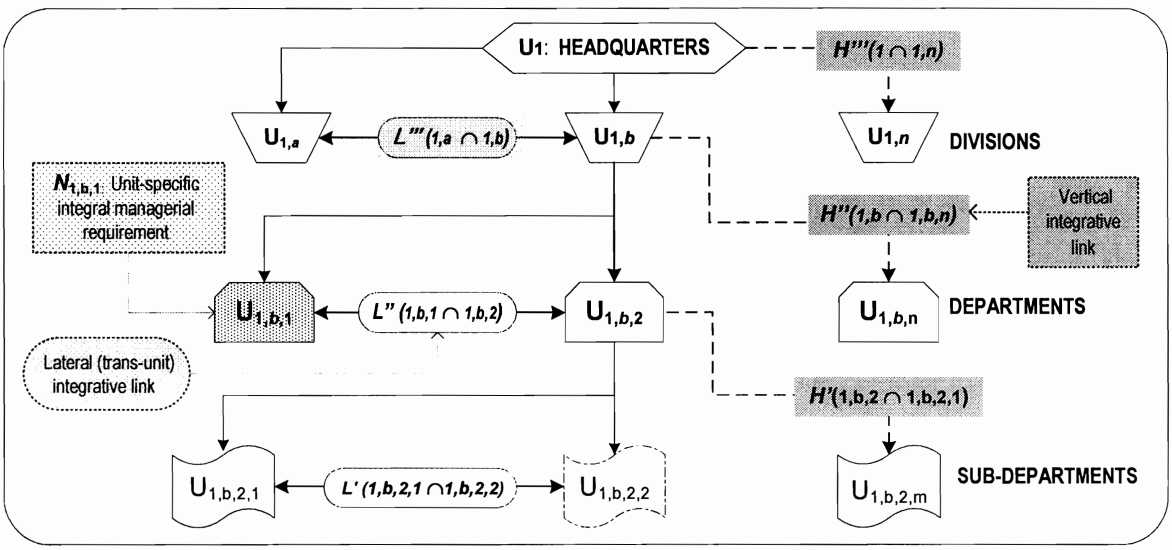

Figure 1: Conventional Organizational Construct

Also shown in Figure 1 are several sorts of managerial requirements. Integral requirements (*N*) originate and remain entirely within a singular organizational unit. Integrative requirements arise in the spaces between entities, and themselves come in two variations, lateral and vertical.

Vertical integrative linkages run along chains-of-command, connecting entities positioned at different levels of the organizational hierarchy. Because the organization portrayed in Figure 1 is a three layer hierarchy, there are three orders of vertical connections: A third-order (*H'''*) connector would conjoin central headquarters with an administrative unit sitting at the immediately next level of aggregation (a division, representing a major functional or geographic unit, perhaps). A second-order vertical connection (*H''*) would then link a second-echelon (divisional) unit with its various departmental level subordinates, and so on. Lateral integrative linkages (*L*) are used to conjoin units positioned at the same level of the organizational hierarchy. There are then three orders of lateral integrative links appearing in Figure 1, with first-order (*L'*) connectors used to link two or more lowest-level organizational units (sub-departments), second-order (*L''*) connectors linking second-echelon (departmental) units and the highest (third-order, *L'''*) lateral linkages effecting inter-divisional intersects.

In earlier specifications of relational model-base structures, the organizational formulation from which relational model-base structures are derived was written as $O \rightarrow D \times E$, where D houses the *regular* decision requirements an organization entails and the members of E are entities, posited to be peers and so all of equivalent authority. Unlike ordinary organizational units (which serve as centers of administrative authority), entities are repositories of decision responsibilities; hence, the assertions underlying relational model-base structures that all integrative links among entities are lateral in orientation and consist solely of decision dependencies in content.

This does not mean that all vertical integration effects will remain unrecognized under relational model-base conventions. There are types of vertical integration rooted in decision-related interactions that should be incorporated into relational model-base structure, such as ties between a dominant and one or more subordinate agencies, or occasions where decision choices made by higher management authorities constrain the search and solution spaces over which lower managers are required or allowed to investigate. However, when covered by relational model-base conventions, these several instances of vertical integration would all be handled as if they were lateral. This is because, under relational model-base conventions, integrative responsibilities are invested in higher-order relational operators. The function of higher-order relational operators is to create and regulate decision dependencies, as do the several entries shown in Table 4 below. An organization can now be redefined one last time as O $\rightarrow \check{R}$ x D x E, where $\check{R}$ is a collection of higher-order relational operators.

Table 4: Orders of Relational Operations

Elementary	Links variables within a decision model: $r(v_m{:}v_n)$ significantly affecting d_x
Primary	Conjoins elementary relational operators: $R(V_x) = (r_1 \cap r_2 \cap \ldots \cap r_z)$
1st Order [Inter-Decision]	Allows for task/entity independent (or *ad hoc)* links between decisions: $R' = d_x \cap d_y \ldots$
2nd Order [Intra-Task]	Indicates intersect conditions for all ($\forall$) decisions comprising a task: $R'' = \forall\ (d_1 \cap d_2 \cap \ldots \cap d_z)$
3rd Order [Inter-Task]	Establishes interconnections between/among two or more tasks: $R''' = R''(K_\alpha) \cap R''(K_\beta) \ldots$

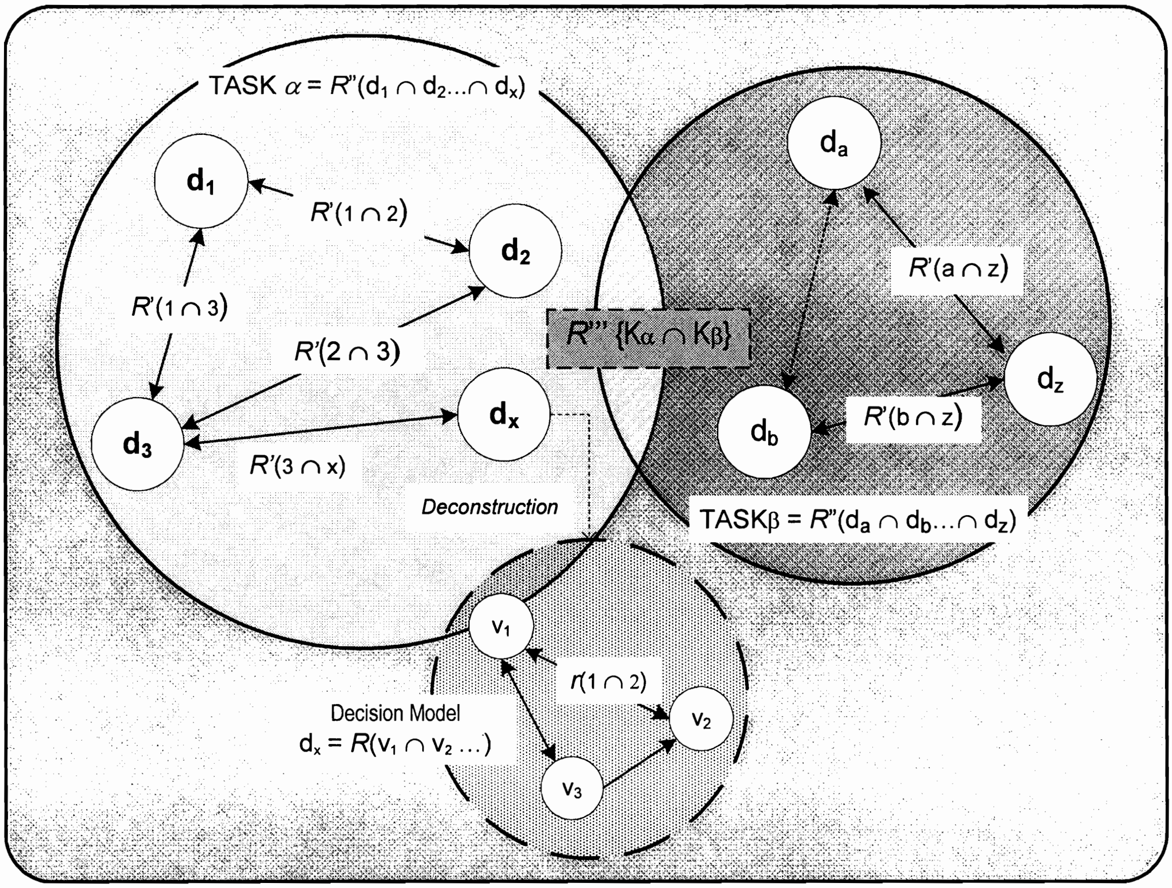

Figure 2: Cellular-Connectionist Portrayal of Relational Operators

The $\check{R}$ x D component is, in effect, a relational model-base structure for which a cellular-connectionist type display like that shown in Figure 2 is appropriate. In cellular-connectionist constructs, the primary focus is on the character and content of the conjunctions among the components of which a system is comprised (mechanical, organic, organizational, conceptual, etc.). For organizations whose management systems rest on relational model-base structures, connective characteristics are captured by relational operators of different orders, with successively higher-order operators (*r*, *R*, *R'*, etc.) distinguished by their more extensive scopes.

Thus, first-order (R') relational operators encode intersect conditions between/among decision instances as $R' = (d_i \cap d_j \ldots \cap d_m)$ or, alternatively, by interconnecting two or more primary relational operators: $R' + (R_x \cap R_y \ldots)$. The symbol $+$ indicates that, rather than subsuming the primary relational operators [which would have been expressed as $R' \supset (R_x \cup R_y)$], R' is superimposed on them. The distinction between a subsumptive and a super-impositional role for higher-order relational operators is important. Were a higher-order relational operator to subsume some number of lower-order relational operators, it would absorb all the intra-decision integrative responsibilities once handled by the lower-order relational operators, as well as being required to cover any inter-decision connections. Under the super-impositional tactic, a higher-order relational operator is responsible only for choreographing the interconnections among lower-order relational operators; the challenge for higher-order relational operators is thus confined to those integrative requirements that remain to be met after the lower-order relational operators have done their work.

As with their elementary (r) and primary (R) counterparts, any R' will include a connective component, C'. Reminiscent of the c-level connectors for elementary relational functions, C' would define different categories of inter-decisional intersect conditions, e.g.: if $C'(d_x{:}d_y) =$

- $\Rightarrow$: Dependency, such that the solution/conclusion for decision d_y is induced/directed by the previously-obtained decision choice for d_x.
- ∇ : Codependency, which has both d_x and d_y subject to, but differentially so, the influence of some superior decision agency.

- $\Leftrightarrow$: Interdependency, which requires congruity between any decision choices that are made with respect to d_x and d_y.

Also like their lower-order r and R predecessors, a first-order relational operator can have a computational component, such that $R' = (C' \cup F')$, where F' is a first-order computational function. The most immediately obvious use for an F' function is to handle cases where the interconnections among decision instances consist of one or more shared variables, such that $(V_x \cap V_y \ldots) = F' \{V\}$.

As for second-order relational operators, their job is to effect connections among the full complement of decision instances comprising a task. In their super-impositional form, they would link two or more first-order relational operators, and so be depicted as $R''_K + (R'd_x \cap R'd_y \ldots \cap R'd_z)$. An R'' operator could also have a second-order functional counterpart (F'') to effect computational connections among the decisions entailed in a task.

Finally, third-order relational operators (R''') are used to connect tasks. A third-order relational operator conjoining all the tasks an organization includes within the organization, $R_o''' = \{R'' \mid K_i \cap K_j\}$, would then define the totality of the lateral integrative requirements to be met in the confines of organization, O. But because each task is itself an assemblage of decision instances, and each decision instance was a subject for the development of a relational substructure, we can expect a transformation whereby $R''' \rightarrow \check{R} \times D$, where the latter term was earlier used as the generative form for a relational model-base structure.

There is an important ancillary aspect to higher-order relational operators, based on the fact that relational model-base structures need accommodate only regular decision instances. Regularity underlies the likelihood of being able to replace elementary and primary relational operators with computational correspondents, giving $r \rightarrow f$ and $R \rightarrow F$. Regular decisions should also regularly allow a first-order categorical connective (C') to be folded into a companion computational expression without any loss of integrity, so enabling $R' \rightarrow F'$. The exchange of first-order relational operators for first-order functions might make it possible to more or less completely automate the realization of inter-decision integrative requirements, invested with the responsibility for actually managing the intersects between and among decision instances. There is also a special significance of second-order connective functions for relational model-base structures. Resulting from $R'' \rightarrow F''$ replacements, they would be formulated as $F''_K = (d_1 \cap d_2 \cap d_3 \ldots \cap d_n)$, where each d_x has an effect on task K, and so used to effect any computational connections among the several decision instances pertinent to a managerial task. A second-order connection function could also be written as $F'' = (F_1 \cap F_2 \ldots \cap F_n)$, which makes more apparent the possibility of F'' functions transforming collections of decision requirements into full-blown decision protocols, allowing for the possibility of the complete automation of conforming managerial tasks.

Manifold Network Models

Media for implementing decision protocols are a type of node-arc construct, configured as what is called a manifold network model. The skeletal structure of manifold network models reflect the procedural properties of a managerial task, specifying which nodes are to be executed in which order under what conditions. But unlike ordinary decision trees, whose nodes typically hold imported numerical items, the nodes of manifold network models will contain algorithmic formulations, which may themselves constitute decision models of the $F(V_x)$ variety. The arcs of manifold network models would serve as avenues of interconnection among the various decision models positioned at the nodes. Pathways for task management protocols could then be made conditional by making the selection of a particular avenue (arc), radiating from a particular node, dependent on the results of the current running of the pertinent nodal algorithms or decision model.

Manifold network models can be assigned to two broad technical categories, recursive and reciprocal. Known as Type 5 manifold network models (Sutherland, 1998), strictly recursive models are hierarchical, allowing only unidirectional, downward lines of influence, and so typically constructed as systems of equations (Ershov, 1998). A Type 5 manifold network model should be technically sufficient for managerial tasks that entail only *dependent* or *codependent* connections among their decisions. Reciprocal manifold network models, known as Type 6, would be able to apprehend reciprocal relationships (interdependencies) among the decision models comprising a managerial task. An example is a neural network, which consist of non-hierarchical, node-arc constructs that can be tuned to comprehend and control non-recursive and non-hierarchical systems (Berry, 1984; Freeman & Skapura, 1991).

In sum, the $R' \rightarrow F'$ and $R'' \rightarrow F''$ replacements spoken of in this last section pose the prospect of relational model-base structures that can not only systematically recognize lateral integrative requirements as decision dependencies, but actively assist in their being met. With lateral integrative requirements being realized, real-time decision capabilities with relational model-base structures become realized.

CHAPTER 4 Case 1: A Type 5 Manifold Network Model in Relational Model-Base Structures: a Hierarchical Application in Precision Agriculture

The methodology of this dissertation involves detailing cases of prototypical relational model-base-centered integrative systems and the incorporated relational model-base structures for each system. A diagram of a generic prototypical relational model-base-centered integrative system appears in Figure 3.

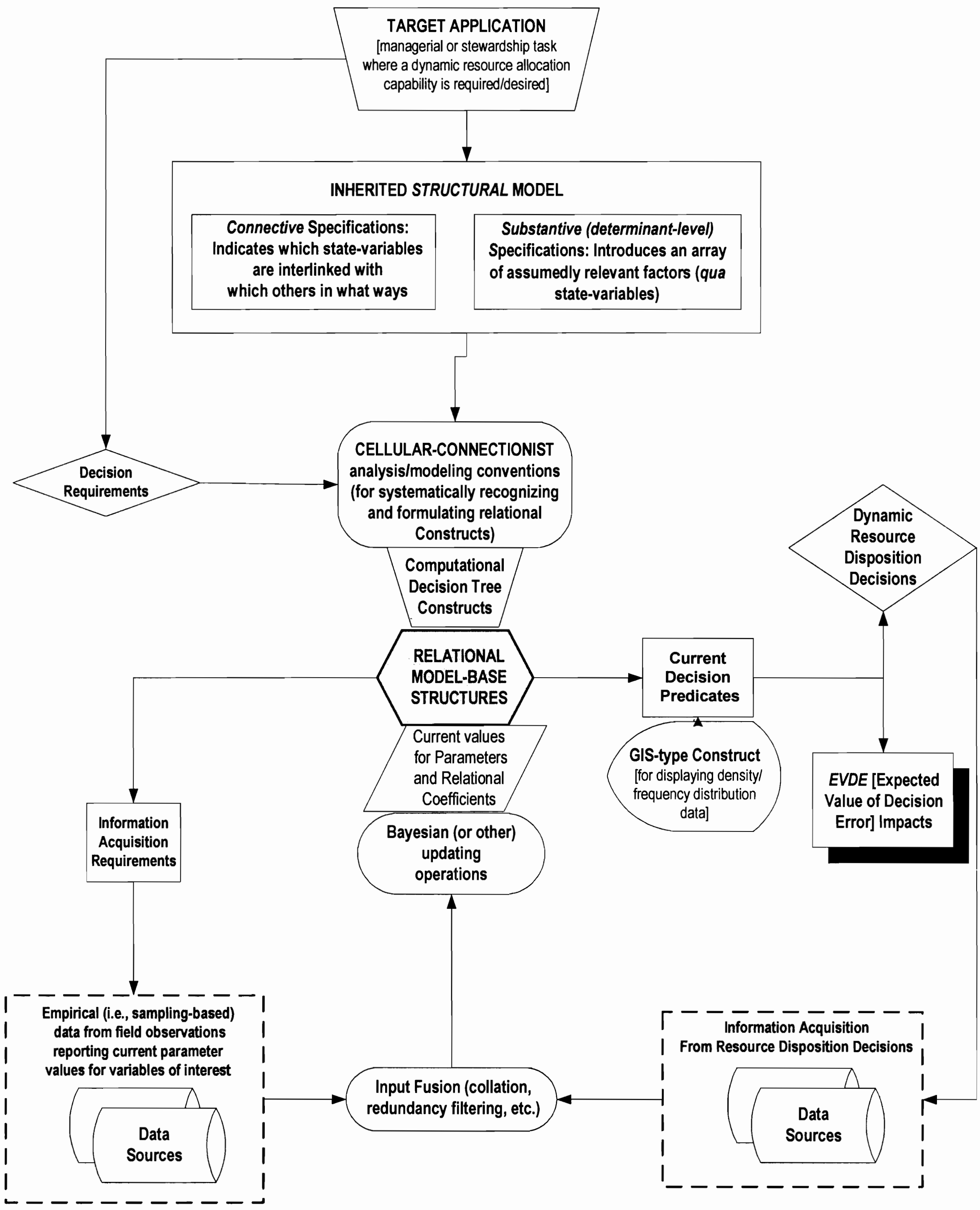

Figure 3: A prototypical relational model-base-centered integrative system

Once the target application has been determined, the remainder of the case is outlined and analyzed by detailing each of the aspects of the diagram as it relates to the particular case for both cases presented in this research. In the context of the recursive relational model-base case and the non-recursive relational model-base case, both contain computational network constructs with node-arc structures, where nodes contain executable decision models and the arcs hold relational functions that explicate any connections between or among the various nodal objects. These relational functions reflect the relationship between decision choices, either dependent, where decision making is hierarchical, or inter-dependent, where decision making is non-hierarchical. In this chapter, a recursive case where the decision choices are dependent or co-dependent will be discussed, while the following chapter will analyze a non-recursive case where the decision choices are interdependent.

The specific instance of dynamic resource allocation using a Type 5 manifold network model outlined here discusses a recursive agribusiness case, with the target application being precision agriculture, alternatively known as precision farming. The goal of precision agriculture is to retain the benefits of large-scale mechanization essential to the large fields (hundreds of meters on a side is typical of today's farm sites), while recognizing local variation within the large field site, both made possible through the increased use of technology. Precision agriculture technologies can lower the cost of production by fine-tuning seeding, fertilizer, chemical and water use, potentially increasing production (Rickman et al., 2003).

Agriculture is one commercial endeavor where there is a clearly identified need to improve operational efficiencies by integrating processes between participants at various levels (Ehmke, Ernst, Hopkins, & Tweeten, 2001). Additionally, the need for real-time information processing to facilitate more efficient agricultural decision making, including the introduction of more sophisticated decision technologies, has also been identified (Hirafuji, 2000; Parlinska & Grabowska, 2002; Schiefer, 2003). The introduction of relational model bases to this scenario would be of tremendous benefit to the practice of precision agriculture, as the computational requirements for decision making in precision agriculture are high in deciding specific amounts and combinations of seeding, fertilizer, chemical and water use for local variations of the large land plots, while the required response time is short, to make certain that the land is optimally planted relatively quickly over ever larger scales. The integration of decision models by the relational model base would allow the farmer to invest decision authority in the relational model base, freeing the farmer to make more strategic decisions about his operation, while simultaneously gaining the capability to more quickly and accurately process the decision inputs acquired to make the decisions.

In this chapter, a recursive, prototypical relational model-base-centered integrative system is going to be detailed from the perspective of a grain producer, including specific requirements for an relational model-base system in this environment. This case qualifies as a recursive case as the grain producer would invariably have a hierarchical decision-making relationship with the grain millers, who establish the requirements for what needs to be produced and in what quantities. As millers improve the efficiency of their processes, the millers have more motivation to establish contracts with producers who are able to provide a consistent product that meets their needs (Zobel, Jones, & Gupta, 2000). The relational model-base system of the grain producer would be hierarchically linked to the decisions of the grain miller on product type and quantity desired, thereby inviting the opportunity for lateral integrative relationships between the two entities involved to optimize decision making, even though the entities are in separate formal organizations.

It is widely identified that integration of the decision-making processes of different supply chain actors is necessary for achieving better operational efficiencies. While the two main actors of grain supply chains, millers and producers, typically base their decisions on different parameters of interest, it is clear that their ability to act efficiently in concert is essential to avoid long-term losses for both participants in the hierarchical supply chain, as well as other participants upstream and downstream in the chain. Goel, Zobel and Jones (2005) propose a multi-agent system for supporting the electronic contracting of food grains, which in this case would act as the intermediary between the grain producer's relational model-base structure and the decision support system of the grain miller. Their proposed system is essentially the foundation of a multi-criteria bid assessment e-commerce program, which allows for open procurement in the restocking function of a real-time inventory management system (as opposed to a restrictive restocking protocol.) This type of system would be one that would have a direct link into the relational model-base system of the grain producer. The agents of the auction would have to get information from the producer's relational model base to be able to proffer various bids, and, once the auction has concluded, the results of the auction would inform the decision requirements within the grain producer's relational model-base-centered integrative system. The outline of this chapter is as follows: after the relational model-base-centered integrative system for the grain producer is detailed, based on Figure 3, the hierarchical relationship between decision models will be shown between the miller and the producer, using the specific example of the multi-agent system proposed by Goel et al. (2005).

A Recursive Prototypical Relational Model-Base-Centered Integrative System in Precision Agriculture

Within the context of precision agriculture and from the perspective of a grain producer, the target application of this integrative system is stewardship over the determination of the amount and placement of a particular crop to be grown on a farm plot (or the combination of crops and in what amount) and the associated amounts of seeding, soil nutrient, pesticides and moisture levels for the given crop, all of which comprise the decision requirements. As rationale for introducing relational model bases to aid in this case, it is important to note how the geographical scale of these decision requirements has increased dramatically for today's farmer. In the United States, a farm operator now manages a square mile or more to be viable, with the size of a typical field measuring hundreds of meters on a side. Usually all portions of that large farm land plot are treated similarly, with crop varieties, seed density, soil preparation, fertilizers, and insecticides (among other chemical treatments) uniformly applied (Rickman et al., 2003). However, grain crops respond to environmental and soil variables that vary on sub-field scales, especially as the farm fields get larger in acreage. To minimize the amount of production lost due to the mismatch of uniform crop treatments and unique physiological responses of individual plants in the crop, the ability to farm more precisely and apply decision requirements for all the associated crop variables on a smaller scale within the farm would be advantageous. Additionally, this associated increase in the scale of geographical decision requirements for precision agriculture has corresponded to a decrease in the response time available for farmers to be able to make these decisions, further highlighting the need for an integrative system to improve and expedite decision making.

In addition to knowing the target application and the decision requirements in the relational model-base-centered integrative system, grain farming comes with an inherent structural model consisting of connective (structural) specifications and substantive (magnitudinal) determinant-level specifications. Connective specifications indicate which state variables are interlinked with which others in what ways. In a real world precision agriculture situation, the complex interplay among decision models governing nutrient absorption, thermal emission of the plants, water absorption and necessary rates of irrigation with relation to precipitation form the connective specifications in precision farming. For each particular farm there would also be substantive specifications, which are the results of the calculation of the initial parameters and algorithmic relationships/constraints relating nutrient, crop and water decisions. These initial substantive (magnitudinal) specifications would be the initial parameters and relational coefficients that would inform the grain producer's relational model-base structure in a real world example. For the purposes of an illustrative example, we will choose four variables relevant to grain farming planting decisions and outline their connective and substantive specifications, which together comprise the inherited structural model for the relational model base, in Table 5. This example will be further explicated in the next section with initial coefficients set for the m_x and b_x variables.

Table 5: Variables, connective and substantive specifications (the inherited structural model) and relational model-base substructure for an illustrative example in precision agriculture

	Inherited Structural Model	**Relational Model-base Substructure**
Variables	v_1: the amount of seed that is planted v_2: the amount of irrigation necessary to achieve optimal soil moisture v_3: the amount of pesticide used v_4: the amount of fertilizer used v_q: amount of grain to be produced	
Connective Specifications (Elementary Relational Operators)	v_2 is $\uparrow$ (positively and proportionally) related to v_1 v_3 is $\uparrow$ (positively and proportionally) related to v_1 v_4 is $\uparrow$ (positively and proportionally) related to v_1 v_2 is $\Rightarrow$ (dependent on (dominated by)) level of current soil moisture, s_o	$\boldsymbol{r_x}$**(1 $\cap$ 2):** v_2 is $\uparrow$ (positively and proportionally) related to v_1 $\boldsymbol{r_x}$**(1 $\cap$ 3):** v_3 is $\uparrow$ (positively and proportionally) related to v_1 $\boldsymbol{r_x}$**(1 $\cap$ 4):** v_4 is $\uparrow$ (positively and proportionally) related to v_1 $\boldsymbol{r_x}$**(2 $\cap$ 3):** v_2 is $\uparrow$ (positively and proportionally) related to v_3 $\boldsymbol{r_x}$**(2 $\cap$ 4):** v_2 is $\uparrow$ (positively and proportionally) related to v_4 $\boldsymbol{r_x}$**(3 $\cap$ 4):** v_3 is $\uparrow$ (positively and proportionally) related to v_4
Substantive Specifications (Computational Functional Relationships	$v_2 = m_2v_1 + s_o + b_2$ $v_3 = m_3v_1 + b_3$ $v_4 = m_4v_1 + b_4$ $v_q = \rho * v_1$, where ρ is the aggregate probabilistic factor that planted seed will produce the anticipated yield.	

A relational model-base structure for a grain producer would also have very specific information acquisition requirements to be able to provide decision makers with adequate accurate and current decision predicates. These requirements would involve the determination or collection of any relevant empirical data necessary to calculate the relational model-base substructure parameters and relational coefficients. On a modern farm, there are several specific pieces of information that need to be known for effective decision making, thus information acquisition requirements would include temperature and composition of the soil, weather conditions on the site, fertilizer residue present in the soil, and moisture conditions of the soil (among others). Knowing the requisite information acquisition requirements in precision farming for the development of more current and accurate data collection directs the ability to tap the appropriate real-time data sources.

The data sources from which the relational model-base structure for the grain producer would gather its information in the precision farming environment will be empirical data (sampling-based) from field observations recording the current parameter values for many variables of interest and historical databases storing information on variables of interest. In the move toward more real-time decision making, it is in this area of real-time field observations where precision farming has made the greatest gains thus far (Rickman et al., 2003). Improved navigation equipment, yield monitors, soil sensors, weather equipment, satellite and cellular network communications, etc., can all be used in a more sophisticated manner to provide decision makers (or technical decision aids, such as relational model-base substructures) with almost instantaneous readings of soil temperature, moisture, precipitation, and pesticide levels, along with many other parametric direct measurement variables that might be of interest. Farmers currently use wireless, high-speed internet services and other forms of wireless, networked communications to link various sensors or grids of sensors placed throughout their vast farm areas to get readings on crop moisture, temperature, weather, soil composition and field conditions, among other things (Hirafuji, 2000; Ninomiya, 2004; Rickman et al., 2003). By having these grids of sensors provide real-time readings of the state of farm conditions, the most current and accurate empirical data can be provided to a relational model-base substructure for decision support.

With the copious amounts of data that will be collected from the field observations and conditions factors, it will be necessary to employ some means of input fusion to reduce the total aggregate of data collected down to the smallest actionable amount. Various methods of data reduction could be used, including collation, redundancy filtering, and templating, as shown in Figure 5. In this agricultural case, various spatial-compilation algorithms, such as GPS correction, would be employed for crop sensor data, as well as correction algorithms for raw yield data, and antenna offsets correction. Each of these input fusion techniques would lead to the eventual output of current values for parameters and relational coefficients of the relational model base.

The Relational Model-Base Structure

The structure of the relational model-base system itself within the recursive relational model-base-centered integrative system will be explicated in detail in this section. All aspects of the integrative system from discussion of the target application and its decision requirements through to the empirical data collection and input fusion leads to the structure of the relational model-base system itself. As the graphic in Figure 3 depicts, the relational model-base system consists of five interrelated parts: the relational model-base structure (the general version of which is described in Table 3); the cellular-connectionist analysis and modeling conventions, for systematically recognizing and formulating relational constructs in the relational model-base structure (the general version of which is depicted in Figure 2); computational decision tree constructs, in the form of a Type 5 manifold network model for this precision agriculture case; the initial substantive specifications of the relational model-base structure consisting of the current values for parameters and relational coefficients (as shown in Table 5 as an illustrative example); and finally, updating operations to continuously update the parameters and relational coefficients of the relational model-base structure based on continuously streaming empirical data from field observations and to perform model modification and selection. Each of these five pieces together forms the comprehensive relational model-base structure central to the relational model-base-centered integrative system.

The cellular-connectionist analysis and modeling conventions in the case of the grain producer, independent of a grain miller, is the necessary beginning of the relational model-base structure. The relational operations in this case build to first-order (inter-decision) operations, allowing for task- and entity-independent links between decisions. As shown in Table 5, at the elementary relational operator level, $r_x(v_m \cap v_n)$ significantly affecting d_x, there are codified links among variables that are related to planting one particular grain (from here on referred to as the planting decision model, d_x): amount of seed that is planted (v_1); the amount of irrigation (v_2); the amount of pesticide used (v_3); and the amount of fertilizer used (v_4). [In a real world example, there would be many other variables that are relevant to this decision, yet for the sake of simplicity, the number of variables in this illustrative example is going to be limited to four.] The relational operators (r) among these variables constitute the decision model for planting, d_x, where $d_x = R_x(v_1 \cap v_2 \cap v_3 \cap v_4)$, which is detailed in Table 5 as the substantive specifications, and

R_x is a primary relational operator conjoining the elementary relational operators, consisting of the system of equations in the illustrative example. For the remainder of this discussion, $r_x(v_m \cap v_n)$ will be abbreviated $r_x(v_m,v_n)$.

Returning to the computational constructs for this model, this hierarchical decision case (as with all Type 5 models) assumes dependent or co-dependent decision-making relationships in the organization that relate to each other and to other participants in the supply chain who might govern what is being farmed and in what quantity. These decision-making relationships are hierarchical and recursive in nature, with the mathematical constructs informing the relational model-base structure operationalizing as a system of linear equations in a hierarchical node-arc structure, where the nodes contain executable decision models (algorithmic objects) and the arcs hold relational functions that explicate any connections between or among the various nodal objects (Sutherland, 1998). The scenario of the grain producer and miller presents no exception to a dependent or co-dependent decision-making model.

Table 6: Configuration Features of Relational Model-Base Substructures for Planting Decision Model (d_x) in Agricultural Case

	Relational Substructure $R(d_x)$			
	$\upsilon_1 = v_{1,t-1}$	$\upsilon_2 = v_{2,t-1}$	$\upsilon_3 = v_{3,t-1}$	$\upsilon_4 = v_{4,t-1}$
$v_1 = v_{1,t}$	ϕv_1	$f(1,2) = f(2,1)$	$f(1,3) = f(3,1)$	$f(1,4) = f(4,1)$
$v_2 = v_{2,t}$	$f(2,1)$: $v_2 = m_2 v_1 + s_o + b_2$	$\phi v_2 = m_2 \phi v_1 + s_o + b_2$	$f(2,3) = f(3,2)$	$f(2,4) = f(4,2)$
$v_3 = v_{3,t}$	$f(3,1)$: $v_3 = m_3 v_1 + b_3$	$f(3,2)$: $v_3 = m_3((v_2-b_2)/m_2) + b_3$	$\phi v_3 = m_3 \phi v_1 + b_3$	$f(3,4) = f(4,3)$
$v_4 = v_{4,t}$	$f(4,1)$: $v_4 = m_4 v_1 + b_4$	$f(4,2)$: $v_4 = m_4((v_2-b_2)/m_2) + b_4$	$f(4,3)$: $v_4 = m_4((v_3-b_3)/m_3) + b_4$	$\phi v_4 = m_4 \phi v_1 + b_4$

In the scenario of the grain producer, the relational model base structure itself would be constructed based on the cellular-connectionist analysis. Table 6 shows a relational substructure of d_x, which in this case is the decision model for planting. Across the top of the grid is the current parameter value for each variable (v_m) which would be initially determined or calculated by empirical field data and over time would be updated through direct observations or through Bayesian updating operations to incorporate new information acquisition data weighting the most recent observations more heavily than older ones. Each row consists of a variable pertinent to the decision model, in this case, v_1, v_2, v_3 and v_4. Where the rows and columns intersect, there is the elementary relational operator, which describes the character and magnitude of the actual or anticipated impact of the current value on that variable. In the case of the grain producer, $r_x(v_2,v_1)$ would signify the relationship/effect of the amount of irrigation (v_2) on the amount of a particular seed that is planted (v_1), which is $r_x(v_2,v_1) = v_2$ is ↑ (positively and proportionally) related to v_1. The value υ_1 at the top of the column would be the current amount of that seed that is being planted, and the value would be updated over time. In this illustrative example, υ_1 is the value of variable v_1 at time (t-1). Based on the substantive specifications, $r_x(v_2,v_1)$ would be replaced by a mathematical or algorithmic expression, $f(2,1)$, where the categorical connectives would be expressed by a mathematical function, as shown for this illustrative case in Table 6.

At this point, it is helpful to outline the time component of v_1 to be able to describe ϕv_1 in the relational substructure table for this example. The iterations of time in terms of running the model relate to the subplots of land the farmer is planting on his planting field, as shown in the Figure 4 below. In two different time periods, the farmer will not be in the same plot of land. If the auction happens at time zero, then t_1 represents the time the farmer plants $plot_{1,1}$, and so on through time until the entire field has been planted, with the decision model being rerun at each point in time.

Subplot of land, $plot_{2,1}$ t_3= planting in $plot_{2,1}$ where farmer is planting grain	**Subplot of land, $plot_{2,2}$** t_4= planting in $plot_{2,2}$ where farmer is planting grain
Subplot of land, $plot_{1,1}$ t_1= planting in $plot_{1,1}$ where farmer is planting grain	**Subplot of land, $plot_{1,2}$** t_2= planting in $plot_{1,2}$ where farmer is planting grain

Figure 4: The entire planting field broken up into subplots which will be planted over time

In this example, ϕv_1 describes the relationship between the variable, v_1, and its value at (t-1), υ_1, at time t. ϕv_1 is defined as the GPS input function including data describing the planting terrain and the amount of seed needing to be planted to achieve $v_{q(1,1)}$, the desired output for that subplot based on the overall amount contracted (v_q). As the farmer plants and navigates throughout his field, differing GPS coordinates processed through a planting map will give the farmer different values for the amount of seed to be planted, based on his location in the field, the amount of seed planted at time t determined by the amount of seed planted up to time (t-1), the expected yield of grain from the seed planted up to time (t-1), the probabilistic equation that applies at that time t, and the total contracted amount v_q. The functions ϕv_2, ϕv_3, and ϕv_4 would be defined similarly in this particular example as the GPS input function with data describing the terrain and ϕv_1 for the respective variable, as detailed in Table 6. Overall, in a real-world example, the entire relational model-base structure, consisting of all the interconnected substructures, would be filled out by all of the variables that had been identified in the cellular-connectionist analysis, reflecting all pertinent relationships in the planting decision model, d_x.

Table 7: Relational Model-Base Output for Planting Decision Model (d_x) in Agricultural Case ($m_2 = 2$; $m_3 = 0.1$; $m_4 = 0.3$; b_2, b_3 and $b_4 = 0$) where if $\rho = 1$, $v_q = 1$ bushel

	v_q	ρ	v_1	v_2	v_3	v_4
t = 1	20	0.6	33.3	66.6	3.33	9.99
t = 2	10	0.5	20	40	2	6
t = 3	30	0.8	37.5	75	3.75	11.25
t = 4	40	0.9	44.4	88.8	4.44	13.32

After all of the data has been processed through the decision-driven relational model-base structure, the current decision predicates (the actual values for v_1, v_2, v_3, v_4) would be available in real time for the grain producer. Table 7 shows the actual values for running the relational model base for the illustrative example, assuming that for each 10 pounds of seed planted, a farmer needs 20 cubic feet of water, 1 pound of pesticide and 3 pounds of fertilizer to produce the desired v_q per subplot, which would give a total production (v_q) of 100 bushels. At each time t, at the planting of each subplot, the amount of seed to be planted is fed in to the relational model base from the data sensors, determined based on the GPS position of the farm plot being planted; subsequently, the model calculates the remaining variables in the model. In a real-world case these predicates would be any output from the relational model base that would inform the decision on how to allocate resources in planting, i.e. the most favorable composition of soil in terms of pesticide and fertilizer amounts, current predicted crop yields, optimal watering strategy, etc. By giving the grain producer this information in real time, he or she is best equipped to make informed and timely decisions in planting. Considering that agriculture is a largely geographical endeavor, some GIS-based construct would be used as the interface where all decision predicates would be displayed to the decision maker, in a format that displays the density or frequency distribution data of relevant variables as mapped onto the grain producer's farm production area. An example of this type of interface is FarmGIS (www.farmgis.com); while this interface is built on top of a relational database system, the same type of interface could be developed for a relational model-base integrative system.

Ultimately, these decision predicates will be used to make dynamic resource disposition decisions, such as how much seed, pesticide, fertilizer and water are needed for a desired crop yield in the illustrative example. These decisions are based on the decision requirements of the relational model-base integrative system. The marked improvement is that with this capability the grain producer would be able to make decisions on pesticide, irrigation and soil treatment based on real-time information provided by the relational model-base structure. Assuming the producer to be risk averse, as he or she needs to provide the exact contracted amount of grain to the grain miller, with any deviation from this amount causing the producer economic loss, the key benefit to the grain producer is a decrease in the impact of expected value of decision error related to the planting. (A further explanation of this is presented later in the chapter.)

As a final piece of the recursive relational model-base-centered integrative system, information acquired from the resource disposition decisions made, which consists of current parameter values resulting from the decision execution, is fed back into the relational model-base structure. This data would be stored outside of the relational model-base structure itself. The quality of previous decisions would be assessed based on different inputs and the outcomes effected. This quality assessment could subsequently be used to generate better decision models, in collusion with the incoming data acquisition requirements. Armed with this information, updating operations would be used to update the relations between the variables (model, or substantive specifications, updating), while Bayesian updating operations would update present operating values for parameters and relational coefficients, examples of which are shown in Table 7. An example of a Bayesian updating operation that could be used here would involve the probability term of the output from seeds planted, ρ. ρ consists of historical values of probability for seed-to-grain output and components from current readings. The example updating operation would be one that weighs the most current value for the probability for seed-to-grain output more heavily than historical values for the probability: $\rho_{now} = (\lambda)\rho_{historical} + (1-\lambda)\rho_{last}$, where $\lambda < 0.5$. Should new data force a significant enough change in the value of a variable that a model alteration or outright substitution that would affect changes in all other variables subject to the original variable's influence would be needed, model specification updating functions, which are ideally dynamic and agent-based in operation, would serve to enact model updating within the relational model-base structure. A model updating function would behave in a way to alter the substantive specifications of the relationship between the variables. If over time, in this example, the relationship between the variables v_1 and v_2 morphed from $v_2 = m_2v_1 + b_2$ to $v_2 = v_1^2 + b_2$, then software agents or some sort of autonomic code generation construct would change the relational substructure (the $f(2,1)$) to reflect the new relationship, $v_2 = v_1^2 + b_2$, and propagate these changes out to any other decision models affected by the model specification update. How parameters and models are updated in a relational model-base structure is shown in Figure 5.

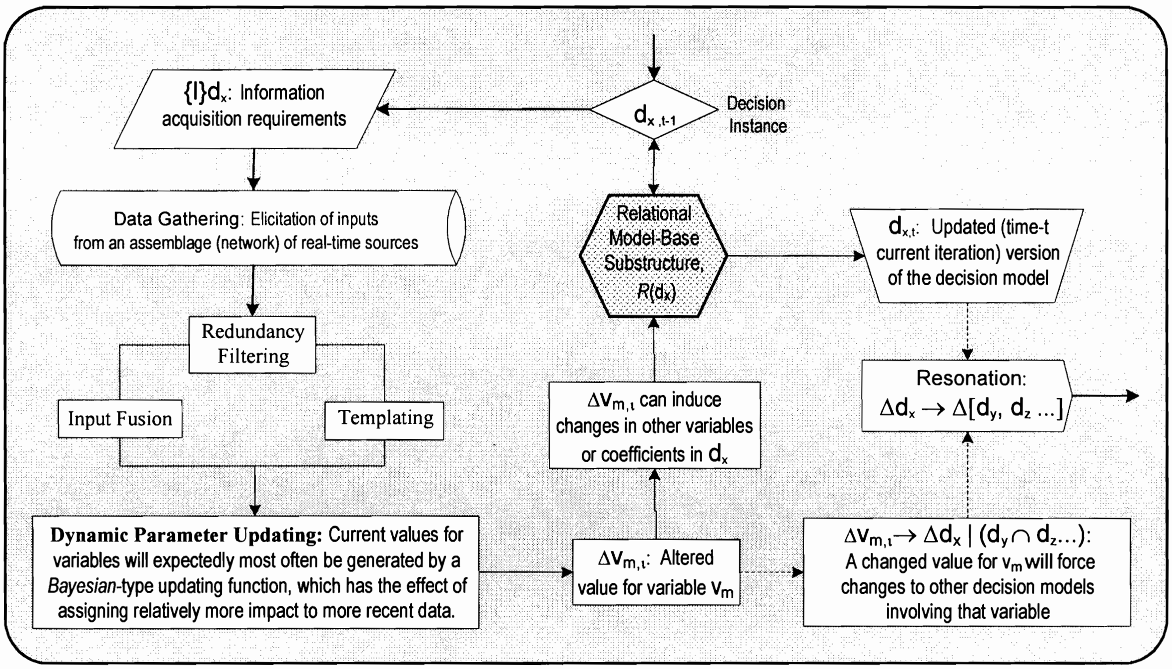

Figure 5: Dynamic Parameter and Model Updating using Bayesian Updating Functions in a Relational Model Base

The Relational Model-Base-Centered Integrative System with the Grain Producer and Grain Miller

Now that the relational model-base-centered integrative system has been detailed for the grain producer, the hierarchical relationship with the grain miller and the multi-agent system for electronic contracting alluded to earlier can be properly introduced. In a broad sense, the grain demands of the miller hierarchically constrain the decision making of the grain producer, as it is the miller who determines which type and what quantity of grain needs to be produced based on the market conditions that the miller is experiencing in terms of demand for products. Although they are not members of the same organizational entity, the grain producer and grain miller do act as laterally-integrated organizational units (a supply chain relationship) that are involved in an intra-task, decision-making relationship, the task of providing grain of the right type and quantity for milling the cereal product demanded by the market. The remainder of this section will discuss the hierarchical decision-making relationship between the grain miller and grain producer in the relational model-base system context and how the multi-agent system proposed by Goel et al. (2005) is involved in the interaction between the two organizational units from the perspective of using relational model-base structures.

The basis of the relationship between the relational model-base structures of a grain producer and a grain miller starts with the view of their interaction as part of an organization, where O → D x E, where D is the set of decision requirements for the task involved of the grain producer providing the miller with the grains the miller is going to purchase, and E is the group of organizational entities within the grain producer and miller's organizations that would be involved in accomplishing the task. Based on a decision tasking table for a relational model-base structure, Table 8 presents the table for this illustrative example.

Table 8: Decision Tasking Table for Illustrative Agricultural Example

	Organizational Entities	
Tasks	**E_1 = grain producer software agent**	**E_2 = grain miller software agent**
K_1 = how much grain of what type is going to be produced	D_{11} = list of decisions that the grain producer makes in determining how much grain of what type is going to be produced, e.g., what plot of land is available to use for this grain; can irrigation, pesticide and seed be acquired; what are the means to acquire these production inputs?	D_{12} = list of decisions that the grain miller makes in determining how much grain of what type is going to be produced, e.g., what response is going to be given to market demand (what products does the miller want to make from this grain and in what quantity)

The organizational entities, E_1 and E_2, would be represented by software agents of the producer and miller, whose behavior would be governed by people within each organization. The task K_1 would involve determining how much grain is going to be produced and of what type. At the intersection of E and K in the table, D represents the list of decision instances involved in task K assigned to organizational entity E. In terms of the agents in the grain contracting case, $D_{(E1, K1)}$, is going to involve the decisions (e.g., d_x, d_y) on quantity made by the producer and executed by the producer agent, where E_1 is the grain producer organizational entity and K_1 is the task of determining how much of a particular grain of what type to grow.[2] The producer agent is going to create bids based on the cost of producing a particular variety of grain and on the risk profile of the producer. The decision list $D_{(E2, K1)}$ is similar; however, it is going to involve decisions made by the grain miller (E_2) on the task of deciding grain type and quantity (K_1) and executed by the miller agent, who is going to accept bids based on variety requirements calculated by the miller. The relational model-base structure of the producer is going to get some of its decision requirements on what to grow and how from the results of this interaction between the miller and the producer. The decision-making relationship is hierarchical in nature, with the precision farming decisions of the grain producer constrained in a top down fashion by the demands of the grain miller.

[2] As outlined in the decision tasking table, Table 1, d_x is a decision instance, which can manifest itself as a decision model, and an element of the D_{nm} set or list.

In this particular precision agriculture case, the entities (E), e.g. conventional business managers, groups of executives, man-machine complexes, or autonomous computer decision devices, in the decision tasking table do not have any direct correspondence with the formal organizational components that appear in typical organizational charts. Indeed, the entities are not part of the same organization, nor do they conform to a formal organizational chart within their own organization. However, this is desirable in this case. Instead of the organizational components representing groups of administrative authority, the entities represent groups of decision-making responsibility. By separating the decision-making entities from the formal organizational units in this case of grain production and having entities from differing organizations participate, the opportunity exists for technical considerations to influence organizational entity relationships, possibly bringing the administrative and technical apparatus between the organizations into better alignment along the supply chain.

In the previous section the configuration features of the relational model-base structure for the grain producer were outlined, and the introduction of the grain miller into this scenario does little to affect that relational model-base structure. When the auction agents of the producer and miller strike a trade, the results of the accepted bid would be incorporated into the decision requirements of the grain producer's relational model-base structure.

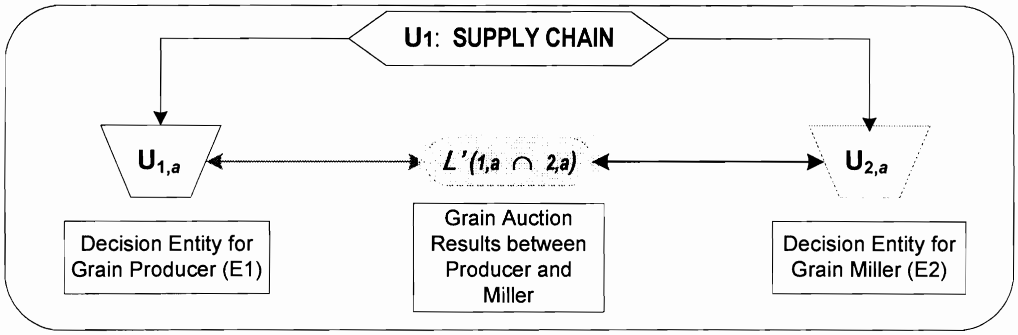

Figure 6: Conventional Organizational Construct for Illustrative Agricultural Example

The most interesting development in this hierarchical case with the introduction of the grain miller is that of the increased lateral integrative requirements between the organizational sub-entities of the grain producer and grain miller. Figure 6 details a conventional organizational construct within this example grain production supply chain. This case introduces a second organization into the supply chain, U_2. Assuming that the decision responsibilities for both the grain miller and producer rest in some group within each organization, the decision entity for the grain producer relevant in the auction (U_1) would be $U_{1,a}$, where "a" designates it as the first of undoubtedly several subdivisions of the grain miller's organization, while the decision entity for the grain miller relevant in the auction (U_2) would be $U_{2,a}$. The entities are from different organizations, but it is not material, as entities are posited to be peers in the overall supply chain and so all of equivalent authority in this decision-making scenario. $U_{1,a}$ is the same entity as E1, which is shown in Figure 6. . Referring back to Table 8, $U_{1,a}$ (E1) is responsible for the list of decisions $D_{(E1,K1)}$ related to Task K, of which d_x is a decision instance, or one of the list of decisions.

It is assumed that both entities want to maximize profit in the transaction; where their interests diverge is that each organization wants the maximum amount of profit for itself. Lateral integration exists across organizations in a hierarchical supply chain relationship, so the lateral relationship of interest would be $U_{1,a} \leftarrow L'(1,a \cap 2,a) \rightarrow U_{2,a}$, where $L'(1,a \cap 2,a)$ is the highest-order, lateral linkage connecting two subdivisions of two distinct organizations entrusted with decision responsibility for each's respective organization, with Figure 6 being a one-layer hierarchy in this example. $L'(1,a \cap 2,a)$ actually consists of the accepted terms at auction in this example, as the agents for both of the entities $U_{1,a}$ and $U_{2,a}$ agree to the terms of which grain to grow and in what quantity to produce that grain for the miller (v_q), forming the lateral integrative linkage between the entities. Time is not a factor in Figure 6; the grain auction results for that particular auction acting as the lateral linkage between the two entities will not change once terms have been agreed upon. However, it is probable that the terms of subsequent auctions (which will serve as lateral linkages at points in time in the future) will change over each iteration of grain auction, and possibly that the results of the prior auctions could be stored in a database for later analysis to determine future bids from the entities, but these storage and organizational learning capabilities would be outside of the relational model-base substructures for the two entities.

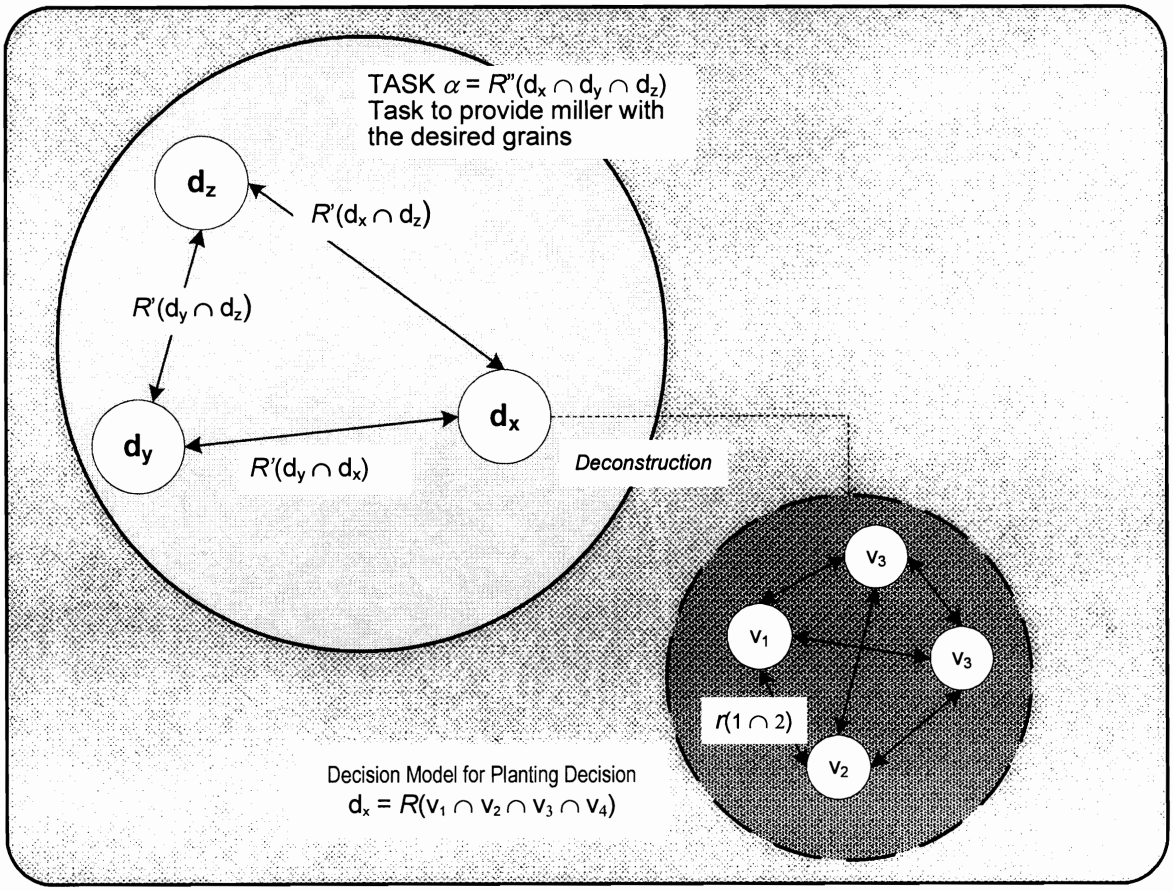

Figure 7: Cellular-Connectionist Relational Model-Base Construct for Illustrative Agricultural Example

While the relational model-base structure for $R(d_x)$ related to the planting decision model of one particular grain does not change with the introduction of the grain miller, it does become necessary to expand the relational model-base structure to include other relational model base substructures, each one relating to any additional decision model. Referring to Figure 7, the decision model for the grain producer alone is d_x, the planting decisions of one particular grain. In addition to the producer's planting decision model for one grain variety (d_x), there is also the total variety decision model for the producer (d_y) and the grain variety decision model for the grain miller (d_z), all of which would use information on grain market conditions to inform the decision models. The grain variety decision model (d_y) would have its own relational model-base substructure, $R(d_y)$, which would include all of the pertinent variables to the decision of, continuing the example, the total amount of grain planted by the grain producer of each grain variety. Planting decisions (decision model, d_x) are interrelated to the decision model of what to plant among varieties of grain (d_y), leading to first-order relational operators (R') encoding the intersect conditions between the planting decisions of one particular grain (d_x) and the decisions of what to plant among varieties of grain (d_y), i.e. $R'(d_x \cap d_y)$, the inter-decision relationships.[3] $R(d_x)$, $R(d_y)$ and $R(d_z)$, the buying decision model of the miller, are outlined in Table 9.

[3] The relational model operating in the intersect between the grain producer and miller might be configured in several ways. Alternative interconnection schemes include a recursive JIT-type construct, a non-hierarchical auction construct (as is outlined in this example), a conventional process control system, a fuzzy-type controller, or a super-impositional production management system. The interconnection might best be configured with a process control construct with a specific function to establish a real-time link – dynamically managing the intersect – between the grower's aggregate (integrated) production management model and the production management model running the mill. This is a concrete example of the instantiation of the conjunction of two relational model-base structures, leading toward the automation of the lateral linkage between the two entities.

Table 9: Decision Models Involved in Task α and their Substantive Specifications

Decision Model	Substantive Specifications for Model
d_x = the producer 1's planting decision model for this particular type of grain (Grain A) in the specific quantity	$R(d_x)$ is the following system of equations: $v_2 = m_2v_1 + s_o + b_2$ $v_3 = m_3v_1 + b_3$ $v_4 = m_4v_1 + b_4$ $v_q = \rho * v_1$, where ρ is the probability that planted seed will produce the anticipated yield.
d_y = the producer 1's planting decision model for the total amount of grain planted of each variety	$R(d_y)$ consists of the following production component decisions: v_q, v_5, v_6, v_7; where v_q is the amount of Grain A output by Producer 1, v_5 is the amount of Grain B output, v_6 is the amount of Grain C output, and v_7 is the amount of Grain D output, in light of capacity constraints on total land available for planting, and total water, fertilizer and pesticide availability for seeds of different types of grains.
d_z = the miller's buying decision model on what quantities of Grain A are needed from each producer	$R(d_z)$ consists of the following buying component decisions: v_q, v_8, v_9, v_{10}; where v_q is the amount of Grain A from producer 1, v_8 is the amount of Grain A from producer 2, v_9 is the amount of Grain A from producer 3, and v_{10} is the amount of Grain A from producer 4

First-order relational operators, i.e. $R'(d_x \cap d_y)$, alternatively expressed $R(d_x) \cap R(d_y)$, would describe intersect conditions among the relating decision models. If these intersect conditions could be described in a mathematical relationship, the *R'* would become a mathematical expression, *F'*. In this example, $F'(d_x \cap d_y)$ is represented with v_q as the same variable in both models (in fact, all three models) and would have the same value at a given point in time that the relational model-base structure was executed.

All intersections of the first-order relational model-base structures would be held in a second-order relational model base structure, *R"*, which in this illustrative example, indicate intersect conditions for all decisions comprising the task of producing the correct quantity of a particular type of grain. Thus, when the grain miller is brought into this model, second-order relational operators (*R''*) are involved (intra-task) to comprise the task of the producer providing the miller with the desired grains (hereafter referred to as Task

α, shown in Table 9). Task α effects connections among the entire group of decision instances comprising this task and link, in this example shown in Figure 7, three first-order relational operators, denoted $R''_{K\alpha} + (R'(d_x \cap d_y) \cap R'(d_y \cap d_z) \cap R'(d_x \cap d_z))$. The intersection in this example consists of v_q being the same variable represented in all three models, signifying the amount of Grain A to be provided by Producer 1 to the miller. In the three models interrelated in Task α, this common variable v_q has the same value in each model. In this illustrative example, v_l is then obtained based on the auction results which outline what v_q must be. Going back to the planting decision model d_x, v_l will be determined based on the probabilistic equation for how much seed to plant to produce how much output, $v_q = \rho * v_l$.

Although in this particular example the intersection only involved one variable, the intersection would also apply to other examples by involving relational operators on all variables that belonged in one of the decision models that also belonged in another relevant decision model to the task, employing the set theory definition of intersection. $R''_{K\alpha}$ could also have a second-order functional counterpart (F''), as partially outlined in Table 9, to effect computational connections among the decisions entailed in a task, most likely in a more realistic example to involve market exchange clearing functions, even in this simple illustrative example in Figure 7 and Table 9. The expanded relational model base for this task structure would comprise components of the relational model-base structures for both the grain producer and the grain miller, with the intersections outlining a hierarchical relationship between the decision instances.

A real-world example of these second-order relational operators would likely involve, among other possibilities, the intersection conditions of one decision model for pesticide application and another model for fertilizer application that were integrated based on the shared variable of soil moisture content within a module that governed the spraying mechanism of a piece of farm equipment. An actual relational model-base-type structure that incorporates several models involved in precision agriculture, the AgLeader Insight Precision Farming System, and its architecture are discussed at length in Chapter 6.

Economic Implications

The goal of the agriculture enterprise is to establish optimal profit margins for the farm. For probabilistic decisions where the decision maker is risk averse, such as those present in the grain contracting case, improvements in the quality of an information base in terms of richness, precision, credibility, and/or currency result in a favorable change in the structure of the associated probability distribution, as shown in Figure 8.

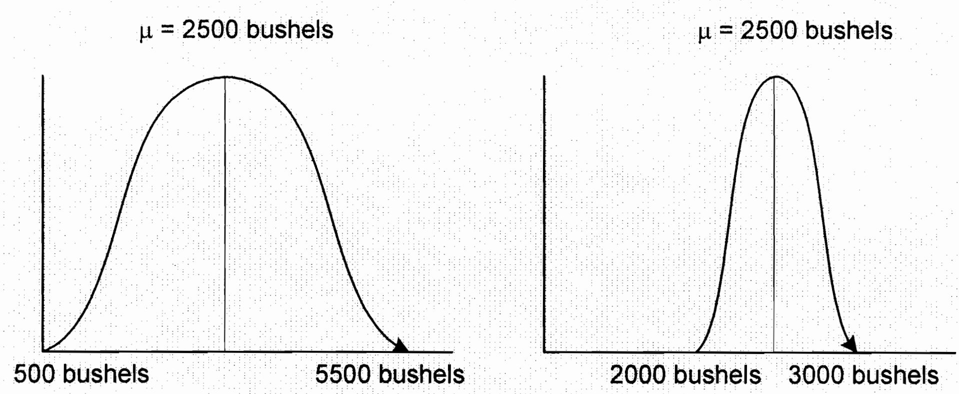

Figure 8a: EVDE of Decision without a Relational Model Base structure

Figure 8b: EVDE of Decision with a Relational Model Base structure

Figure 8: The Expected Value of Decision Error using a Relational Model-Base Structure ($\mu = v_q$)

The distribution in Figure 8b, driven by an improved information base provided by the relational model-base structure, with its updating operations for model specification and parameter updating, entails a lower expected value of the decision error on v_q than the distribution in Figure 8a, which is based on a less complete information base. In both distributions, μ, or v_q, is taken as the amount of grain that needs to be provided by the grain producer to satisfy the completed bid with the grain miller. The key difference between the two distributions is Figure 8b's much narrower range of production values that are deemed possible. This contraction is presumed to be a consequence of additional valuable information contained in the underlying information base of Figure 8b. This results in a reduction in the expected value of decision error (EVDE), defined as the probability multiplied by loss for all $| \mu-\alpha |$, where α is any value included in the range of the probability function.

When analyzing how to minimize the expected value of decision error, the probability function broken out in terms of the different subplots in planting is helpful. Referring back to Figure 4, the total anticipated output, v_q, is equal to the sum of the expected outputs for all of the subplots, $vq = v_{q(1,1)}+ v_{q(1,2)}+ v_{q(2,1)}+ v_{q(2,2)}$. Although there are several ways to choose component values of each subplot, for this example, the component values for the v_q of each subplot were selected based on the probability for each subplot to produce the desired amount of grain. More seed was planted where the probability was higher that the output could be maximized. When incorporating error into this equation, it becomes $v_q = (\rho + \varepsilon)v_1$. v_q, which will be equal to the sum of the anticipated output from each of the individual subplots, will now be equal to: $[\rho_{1,1}v_{1(1,1)} + \varepsilon_{1,1}v_{1(1,1)}] + [\rho_{1,2}v_{1(1,2)} + \varepsilon_{1,2}v_{1(1,2)}] + [\rho_{2,1}v_{1(2,1)} + \varepsilon_{2,1}v_{1(2,1)}] + [\rho_{2,2}v_{1(2,2)} + \varepsilon_{2,2}v_{1(2,2)}]$. Minimizing the expected value of decision error is accomplished by minimizing the ε terms in the equation, which represent EVDE.

The distribution in Figure 8b has a lower EVDE than that in Figure 8a because the worst that is expected to happen is that there would be a loss (real or opportunity) of 1000 (vs. 5000) units. Thus, the value of information from the relational model base that is seen as an improvement over information provided from current systems is equal to the EVDE (area in Figure 8a – area in Figure 8b). Thus, to the extent that the relational model-base structure on any level can provide an improved information base that will reduce the EVDE and provide tightening and elimination of bias in the mean, moving to a relational model-base structure to facilitate organizational decision making is valuable to any organization that implements it.

In this economic case of the grain producer and grain miller, adopting relational model bases as a technical tool for adopting a real-time approach to organizational decision making is only desirable to the extent that it can be expected to result in a net reduction of the expected value of decision error. As the result of the accepted bid in the grain contracting auction, the quantity and type of grain needed by the producer are known and fixed, with all of the negotiation completed prior to the offering and acceptance of the bid. In this situation, the grain producer is going to be risk averse in that he will not want to grow any more or any less of that particular grain (as that would have no additional marginal utility to the producer.) Therefore, the move to relational model-base decision technology must provide value through giving real-time information, so the degree of variance between the expected grain yield and actual grain yield can be minimized, thereby restricting the expected magnitude (or severity) of the negative impact from any errors that are made. Although it would be improbable to expect complete information in the grain producer's scenario (especially with respect to uncontrollable variables, such as weather conditions), the relational model-base structure and the superimposed higher-order relational model-base structure with respect to the grain miller can reasonably be expected to provide more timely and accurate information than would be otherwise available. This allows the grain producer to reduce the expected value of decision error, and therefore, make better predictions and reduce risk.

Within the context of a grain producer's decision making with respect to precision agriculture, providing enhanced real-time information and being able to incorporate feedback from previous resource allocation decision outcomes in a more integrated and timely manner gives the grain producer a better decision technology than he or she has had previously. A relational model-base structure, as part of a larger relational model-base-centered integrative system applied to the decision domain of precision agriculture, would provide grain producers with real-time production information, in addition to allowing for better lateral integration than what is currently available in decision making with grain millers (Goel et al., 2005). This enhanced integration is achieved through a closer technical decision predicate relationship made possible by the intra-organizational grain producer relational model-base structure and the higher-order relational model-base structures that operationalize the decision-making relationship between the grain producer and the grain miller.

CHAPTER 5 Case 2: A Type 6 Manifold Network Model in Relational Model-Base Structures: a Non-hierarchical Application in Ecological Economics

In this chapter, a prototypical relational model-base-centered integrative system anchored in ecological economics and based on a Type 6 manifold decision model will be explicated, similar to the analysis in the previous chapter. Type 6 models assume interdependent decision-making relationships among organizations with no single organization having the authority of forcing exogenous constraints on another, such as aspects where various ecological interests all over the world have to make interdependent allocation decisions and where land development concerns rival preservation concerns. This particular case analysis will discuss competing interests in land conservation and development.

Within the case analysis, the computational decision tree constructs for a Type 6 manifold decision model will be a computational network with nodes as computational elements (functions or systems of equations), somewhat similar to a high-end neural network. From a technical perspective, the entire prototypical relational model-base-centered integrative system would allow for the relational model-base structure with the proper decision tree constructs to provide three key operational capabilities among non-hierarchically related entities: 1) to allow multiple system participants to develop a consistent, precise and reliable "snapshot" of the decision predicates in a decision-making scenario; 2) to allow decisions to be coordinated among system participants in real time; and 3) to distribute decision outcome information, when available, among all decision makers so that one decision entity can respond to a system situation, even if that decision entity does not have the decision predicate information locally (Busch & Grant, 2003).

This case of dynamic resource allocation using a Type 6 manifold network model is that of a non-recursive ecological economics case, with the target application being preservation of biodiversity through land (habitat) protection. The two entities that would be non-hierarchically related in this preservation effort are the environmental conservation group and the corporate entity interested in utilizing resources on that land for profit maximization of that corporate entity itself. In the case discussed in this chapter, relational model bases are applied to facilitate decision making, with relational model-base outcomes based on functional resolutions of the conflicts that arise between these two entities, as opposed to purely subjective public policy resolutions. Often in the ecological economics domain there is not enough detailed or current information to resolve disputes in any technical way (Morrison, Marcot, & Mannan, 1998), leading to a decision-making process easily swayed by more subjective predicates, such as public opinion or current political fashion under democratic capitalist conventions. The application of relational model bases to this case in the ecological economics domain will make possible and facilitate decision making based on objective decision predicates, as opposed to the more subjective decision predicates currently in use, from where complaints of the politicization of science emerge. Relational model bases can help to make more objective the management of conflicting motives, instead of relying strictly on resolution by socio-economic convention, e.g. voting and majority rule.

For this case the allocative rationality of land use is the dominant decision-making criterion. Preserving land means preserving more future options for how to economically maximize use of the land across various constituencies, avoiding exploitation. Land preservation is an urgent focus at the nexis of ecology and economics. More important in the survival equation than population growth, resources and food scarcity, or even pollution, is the tendency throughout the world to increase industrial development as rapidly as possible (Miller, 2003). At first glance, from a policy-making perspective, rapid industrial development might appear to be the path toward increased standards of living for a population; with further investigation, it becomes clear that the cost to the public good of the environment is not in all cases outweighed by the benefit to the population. A critical assumption underlying classical economics – that if the best interests of all individuals are served, then the overall economic best interest is served – is therefore problematic in ecological economics. The bias in decision making towards the short run and local as the result of that economic tenet has a significant detrimental effect on ecological interests, interests that in the long run affect all individuals. Not only in the area of habitat protection and utilization, but throughout environmental economics, classical economics is failing (Hawkin, 1993). Economic models generally do not take into account the "value" of damage done to the environment, regardless of that system being socialist or capitalist.

Most modern day market economists do not do a very good job at assessing the actual values of planetary resources upon which we all depend (Miller, 2003).

Establishing a framework where the goals of an organization whose function is to steward the environment can be balanced with the goals of an organization whose function is to maximize their profit on land to be developed is essential to improving decision making in ecological economics. A means of conducting better habitat management over time, the adaptive management approach (Morrison et al., 1998) lacks technical capacity within it, which is a key problem hindering its successful application in managing wildlife habitat and ecosystems (Hilborn, 1992; Lee, 1993). Without this technical capability, operational implementation of the adaptive management approach is hindered, and optimal outcomes in ecological economics cannot be realized. Relational model bases can be applied as technical capacity for ecological management. The two non-hierarchically related entities, the conservation group and the corporation, would each have a relational model-base structure governing their own internal decision-making processes, and these two relational model-base structures would provide inputs to the relational model-base structure for a third entity who would be ultimately responsible for the decision making for land preservation, usually a government entity.

It is important to note that even though a third party entity ultimately makes the decisions, the inputs from the environmental steward and the corporation should not be weighted *a priori* in the government entity's relational model-base structure, if for the inputs were weighted in some way, the relationship between the two entities would revert to some type of hierarchical relationship, eliminating the impetus for this case. Ideally, the weighting of the various inputs from the two entities would be functionally resolved within acceptable ranges autonomously and not resolved by public policy, although realistically, the weightings of outputs would have to conform to some hierarchy of possibilities. The adaptive management approach for habitat and ecosystems would most likely be effective in considering input from both entities without resorting solely to potentially biased public policy to dictate decision predicates or benefiting individual weighting solutions with the technical capacity that relational model bases provide in allowing for real-time, quantitative data relevant to the problem domain be used as objective decision predicates.

A Non-Recursive Prototypical Relational Model-Base-Centered Integrative System in Ecological Economics

In the context of ecological economics, the target application for this non-recursive relational model-base-centered integrative system is habitat protection and utilization through land preservation. (See Figure 3 for a generic prototypical relational model-base-centered integrative system.) From a conservation perspective, habitat provides the basis for wildlife conservation, but it does not ensure it. Maintenance of habitats and wildlife populations is only one facet of maintaining overall biological diversity, but a crucial one. From the perspective of a corporation, land for development (versus exploitation) provides the necessary room for industrial growth to build offices, manufacturing plants, even the housing needed for all of the additional employees who will occupy the offices and factories. In the face of these two competing and non-hierarchical entities, decision-making authority for land stewardship falls to various government entities. These government entities take input from both the conservation groups and the corporations to make final decisions on land resource allocation. This illustrative case has been simplified to discuss the interface of only one conservation group and one corporation being mediated by one government entity (or other societal agent), although in a more realistic scenario, there would be many conservation interests and several corporations all providing input to one or more governmental entities who mediate land disposition and allocation. The core relational model-base structure that is described in this case is the one resident within the societal agent acting as environmental steward (often a government entity), which would provide real-time decision predicates for ultimate decisions on land allocation.

Table 10: Variables, connective and substantive specifications (the inherited structural model) for an illustrative example in ecological economics

	Inherited Structural Model	Relational Model-base Substructure
Variables	v_1: the number of species (S) v_2: a scaling constant that varies by group and location (C) v_3: the rate at which the number of species increases with increasing area (z) v_4: the resource patch area (A)	
Connective Specifications (Elementary Relational Operators)	v_1 is $\uparrow$ (positively and proportionally) related to v_4 v_1 is $\Uparrow$ (more than proportionally positively) related to v_3 v_2 is $\Rightarrow$ (dependent on (dominated by)) v_1 and v_4	$r_x(1 \cap 2)$: v_2 is $\Rightarrow$ (dependent on (dominated by)) v_1 $r_x(1 \cap 3)$: v_1 is $\Uparrow$ (more than proportionally positively) related to v_3 $r_x(1 \cap 4)$: v_1 is $\uparrow$ (positively and proportionally) related to v_4 $r_x(2 \cap 3)$: v_4 is $\uparrow$ (positively and proportionally) related to v_1 $r_x(2 \cap 4)$: v_2 is $\Rightarrow$ (dependent on (dominated by)) v_4 $r_x(3 \cap 4)$: v_3 is $\leftrightarrow$ (co-determinant with) v_4
Substantive Specifications (Computational Functional Relationships	$S = CA^z$, or $v_1 = v_2 v_4^{v_3}$ (When plotted in a log-log relationship, the equation becomes: $\log v_1 = \log v_2 + v_3 \log v_4$)	

The inherited structural model for this non-hierarchical case, consisting of connective and substantive specifications for land preservation (habitat conservation) as shown in Table 10, rests in species area relations. The species area curve provides a relationship between the number of species and the resource area involved (Rice & Kelting, 1955). At its simplest, the number of species, S, is affected by the resource patch area, A, according to the equation: $S=CA^z$, where C is a scaling constant that varies by group and location, and z is the rate at which the number of species increases with increasing area. When plotted on a log-log relationship, the equation becomes, $\log S = \log C + z \log A$, with z varying from 0.24 to 0.49 (MacArthur & Willson, 1967). As a result of the findings of the z factor, as a general rule of thumb, twice the number of species require ten times the area (Darlington, 1957; Harris, 1984). Throughout the ecological management literature, many cautions have been leveled at interpreting species area relations and incidence functions of individual species, leading to conflicts between conservation groups and corporate interests. The foremost caution is that of sampling effect, or the chance inclusion of a given species in a large area, simply due to having more area "sampled." Additionally, most ecological studies provide only a snapshot of systems in transition and do not reveal the trend of species richness levels or species occupancy rates, influenced by seasonality and other factors. Perhaps the most contentious aspect of interpreting the species area relation among competing interests is the importance of the species-specific effect of habitat contributed by adjacent lands. This boundary effect can complicate interpretation of the effects of management policy in wildlife, but must be considered when devising land resource allocation plans that account for effects across ownership boundaries (Morrison et al., 1998), to link stewardship sites, allow for migration corridors, etc. How the government, a conservation group and a corporate entity laterally integrate within inter-organizational constructs to make decisions on land and habitat and a specific, illustrative example of the relational model-base structure based on the species area curve will be discussed in this case.

The decision requirements for the target application of habitat protection and land utilization would involve land resource allocation. Each constituency, both the conservation group and the corporate interest, will have certain outcomes that it would like to see occur, and the decision requirements are the amount and location of the land to be allocated and for what purpose. These requirements would inform the cellular-connectionist analysis done as the basis of the relational model-base structure itself. The information acquisition requirements would involve the determination of any relevant empirical data that needs to be collected to calculate the relational model-base substructure parameters and relational coefficients. In the context of habitat conservation and land allocation decisions, information acquisition requirements would include the number of species resident in a parcel of land, the amount of land and at what location does the affected land lie in relation to the species' habitats, among others. The unique nature of this non-hierarchical relational model base would require that information be acquired from both the data systems of the conservation group and the corporate entity, in addition to external data sources, such as satellite-based land surveys, and brought into the relational model base of the government entity. Therefore, it would be crucial to ensure that the data be as objective as possible, as each group could have different values for the same information acquisition requirement. What would make the relational model base resident in the government entity unique and of great import as a technical decision aid in this case is that the government entity could validate empirical data inputs to its relational model-base structure to make objective decisions based on outputs from its relational model-base substructure.

Initially, studies would be conducted or other scientific data would be used to give the beginning values of the number of species involved on the area of land concerned to fully inform the inherited structural model. Over time, additional empirical data from field observations would be collected to keep the relational model-base substructure parameters updated based on current conditions affecting the land resource area. Again, it would be critical to ensure that all information acquisition requirements be as objective as possible, preferably empirical and directly acquired, to ensure that neither entity, the conservation group or the corporate interest, is able to bias the inputs to the relational model-base substructure of the mediating government entity. Ultimately, the more involved the competing parties are in data collection and analysis, the more they communicate with one another, enhancing the possibility that the information acquired for the relational model base will be acceptable to both parties (Morrison et al., 1998).

As output of the government entity relational model base, the current decision predicates from that relational model base would be displayed in a GIS construct. In this case, the area of interest is land, making GIS outputs of land disposition requirements straightforward. As various parameters changed, such as the number of a particular species or the dollar value of potential development, the current decision predicates would be displayed using a GIS system. This type of visual display output supplied with real-time information from relational model-base results would provide organizational decision makers, or an allocating model invested with decision authority, with clear and concise information from which to make decisions. A GIS makes it easier to visualize the spatial diversity of resources, to integrate outputs from the relational model-base substructure and to assess the impact of prior resource disposition decisions, thereby enhancing the transparency of decisions regarding natural resource use. Although the GIS application is not able to resolve value-based conflicts (in this case, the relational model-base substructure is relied upon to technically accomplish that, if possible), the GIS application is helpful in defining spatial and natural resource conflicts.

These decision predicates displayed in the GIS interface will be used to make dynamic resource disposition decisions based on the decision requirements that were outlined as decision requirements of the integrated relational model-base-centered system. The government entity would have the technical capability to make decisions on land resource allocation and disposition with respect to ecological and corporate considerations, with the technical capacity based on real-time information provided by the relational model-base structure. The key economic benefit to the government entity is a decrease in the impact of expected value of decision error related to land disposition.

The Relational Model-Base Structure

The structure of the relational model-base system itself within the non-recursive relational model-base-centered integrative system will be explicated using an illustrative example in this section. All aspects of the integrative system from discussion of the target application and its decision requirements through the empirical data collection and input fusion leads to the structure of the relational model-base system itself. As described in the previous chapter, the relational model-base system substructure consists of five interrelated parts: the relational model-base substructure; the cellular-connectionist analysis and modeling conventions, for systematically recognizing and formulating relational constructs in the relational model-base structure; computational decision tree constructs, in the form of a Type 6 manifold network model for this ecological economics case; the initial substantive specifications of the relational model-base structure consisting of the current values for parameters and relational coefficients; and finally, updating operations to continuously update the parameters and relational coefficients of the relational model-base structure based on continuously streaming empirical data from field observations and to perform model modification and selection. Each of these five pieces forms the comprehensive relational model-base structure central to the relational model-base-centered integrative system.

The cellular-connectionist analysis and modeling conventions in the case of the government entity, independent of the conservation group and the corporate interest, is the necessary beginning of the relational model-base structure. The relational operations in this case build to first-order (inter-decision) operations, allowing for task- and entity-independent links between decisions. As shown in Table 10, at the elementary relational operator level, $r_x(v_m \cap v_n)$ significantly affecting d_x, there are codified links among variables affecting habitat diversity (from here on referred to as the habitat conservation decision model, d_x): v_1 is the number of species in the designated area (S); v_2 is a scaling constant that varies by species and location (C); v_3 is the rate at which the number of species increases with increasing area (z); and v_4 is the resource patch area (A). [There are certainly other variables that are relevant to this decision, yet for the sake of simplicity in this illustrative example, the number of variables here is going to be limited to those in the species area curve equation.] The relational operators (*r*) among these variables, detailed in Table 10, constitute the decision model for land conservation, d_x, where $d_x = R_x(v_1 \cap v_2 \cap v_3 \cap v_4)$, which is detailed in Table 10 as substantive specifications, and R_x is a primary relational operator conjoining the elementary relational operators. In this illustrative example, the elementary relational operators are governed by the mathematical expression $v_1 = v_2 v_4^{v3}$; therefore, their relationship can be demonstrated in the relational model-base substructure with this *f*-expression. For the remainder of this discussion, $r_x(v_m \cap v_n)$ will be abbreviated $r_x(v_m,v_n)$.

Ultimately, as will be detailed later in the chapter when discussing lateral integrative requirements between the conservation group and corporate interest to perform this land allocation task, habitat conservation decisions (decision model d_x in this case) are interrelated to the decision models of extracting commercial value from the land (d_y), leading to first-order relational operators (R') encoding the intersect conditions between the habitat conservation decision model (d_x) and the commercial land value extraction decision model (d_y), i.e. $R'(d_x \cap d_y)$, the inter-decision relationships. When the government entity is brought into this model, second-order relational operations are involved (intra-task) to perform the task of land use allocation. With output from the relational model-base substructure, the government entity would perform the task, with inputs to each decision model from both the conservation group and the corporate entity.

Returning to the computational constructs for this model, this non-hierarchical decision case (as with all Type 6 models) assumes interdependent decision-making relationships among the organizations, as demonstrated by the non-hierarchical relationships between the conservation group, the corporate interest, and the government agency responsible for enacting the task. The non-hierarchical nature of these interdependent decision-making relationships are represented by mathematical constructs forming the relational model-base structure, operationalized as a system of equations in an unlayered, non-hierarchical node-arc structure, where the nodes contain executable decision models (algorithmic objects) and the arcs hold relational functions that explicate any connections between or among the various nodal objects (Sutherland, 1998). As no constituency holds power over another and all groups have to contribute input to the decision in concert with one another (their interdependency), the values that would govern the ultimate output would optimally be functionally resolved, having the outputs be governed by ranges of acceptability derived from the inherited structural models for this case.

Table 11: Configuration Features of a Relational Model-Base Substructure for the Habitat Conservation Decision Model (d_x) in the Ecological Economics Case

	υ_1	υ_2	υ_3	υ_4
v_1	ϕv_1	$f(1,2) = f(2,1)$	$f(1,3) = f(3,1)$	$f(1,4) = f(4,1)$
v_2	$f(2,1)$: $\log v_2 = \log v_1 - v_3 \log v_4$	ϕv_2	$f(2,3) = f(3,2)$	$f(2,4) = f(4,2)$
v_3	$f(3,1)$: $v_3 = (\log v_1 - \log v_2) / \log v_4$	$f(3,2)$: $v_3 = (\log v_1 - \log v_2) / \log v_4$	ϕv_3	$f(3,4) = f(4,3)$
v_4	$f(4,1)$: $\log v_4 = (\log v_1 - \log v_2) / v_3$	$f(4,2)$: $\log v_4 = (\log v_1 - \log v_2) / v_3$	$f(4,3)$: $\log v_4 = (\log v_1 - \log v_2) / v_3$	ϕv_4

In the scenario of habitat preservation and land allocation, the relational model-base substructure would be constructed based on the cellular-connectionist analysis. Table 11 shows a relational substructure of d_x, which in this case is the decision model for habitat/species preservation. Across the top of the grid is the current variable value for each variable (υ_m) which would initially be determined or calculated by empirical data and over time would be updated through direct observations or through Bayesian updating operations. Each row consists of a variable pertinent to the decision model, in this case v_1, v_2, v_3, and v_4. Where the rows and columns intersect, there is the elementary relational operator, which describes the character and magnitude of the actual or anticipated impact of the current value on that variable. In this case, $r_x(v_1,v_2)$ would signify the relationship/effect of the scaling constant (v_2) on the number of species in the designated area, based on the current value of v_3 (υ_3). The value of the variable at the top of the column, υ_1, would be the current number of species in the designated area, and the value would be updated over time. Because both of these variables are present in the species area curve, a quantitative relationship exists that allows the replacement of $r_x(1,2)$ with $f(1, 2)$. Indeed, all of the elementary relational operators in Table 11 have been quantified to reflect their relationship in the species area curve. In a real world example, this relational model-base structure would be filled out by all of the variables that had been identified in the cellular-connectionist analysis, reflecting all pertinent relationships in the habitat preservation decision model, d_x.

Table 12: Relational Model-Base Output for Habitat Conservation Decision Model (d_x) in Ecological Economics Case $v_1 = v_2 v_4^{v3}$, assuming v_3 (z) = 0.25 and v_2 (C) = 5.4 (looking at larger areas each time in sq. m.)

	v_1	v_2	v_3	v_4
t = 0	5	5.4	0.25	1
t = 1	6	5.4	0.25	2
t = 2	7	5.4	0.25	3
t = 3	8	5.4	0.25	4
t = 4	9	5.4	0.25	8
t = 5	10	5.4	0.25	12
t = 6	11	5.4	0.25	16

After all of the data has been processed through the decision-driven relational model-base structure, the current decision predicates (the actual values for υ_1, υ_2, υ_3, υ_4) would be available in real-time for the government entity. Table 12 shows the actual values for running the relational model base for the illustrative example. At each time t, the amount of area to be analyzed for number of species present (υ_4) is fed in to the relational model base by the habitat analysts and developers; subsequently, the model calculates the remaining variables in the model. In a real-world case these predicates would be any output from the relational model base that would inform the decision on how to allocate land for development/preservation. By giving the governmental entity this information in real time, it is best equipped to make informed and timely decisions in land allocation. Considering that dynamic resource allocation of land is a geographical endeavor, some GIS-based construct would be used as the interface where all decision predicates would be displayed to the decision maker(s), in a format that displays the density or frequency distribution data of relevant variables as mapped onto the development area being analyzed.

Ultimately, these decision predicates will be used to make dynamic resource disposition decisions for land allocation, with these decisions based on the decision requirements of the relational model-base integrative system. As a final piece of the recursive relational model-base-centered integrative system, information acquired from the resource disposition decisions made, which consists of current parameter values resulting from the decision execution, is fed back into the relational model-base structure. This data would be stored outside of the relational model-base structure itself. The quality of previous decisions would be assessed based on different inputs and the outcomes effected. This quality assessment could subsequently be used to generate better decision models, in collusion with the incoming data acquisition requirements. Armed with this information, updating operations would be used to update the relations between the variables (model, or substantive specifications, updating), while Bayesian updating operations would update present operating values for parameters and relational coefficients, examples of which are shown in Table 12. For this example, the updating operations would execute a change in the variables v_2 or v_3, should the properties of the land being analyzed change. Should new data force a significant enough change in the value of a variable that a model alteration or outright substitution would be needed, one that would affect changes in all other variables subject to the original variable's influence, model specification updating functions, which are ideally dynamic and agent-based in operation, would serve to enact model updating within the relational model-base structure. How parameters and models are updated in a relational model-base structure is shown in Figure 9.

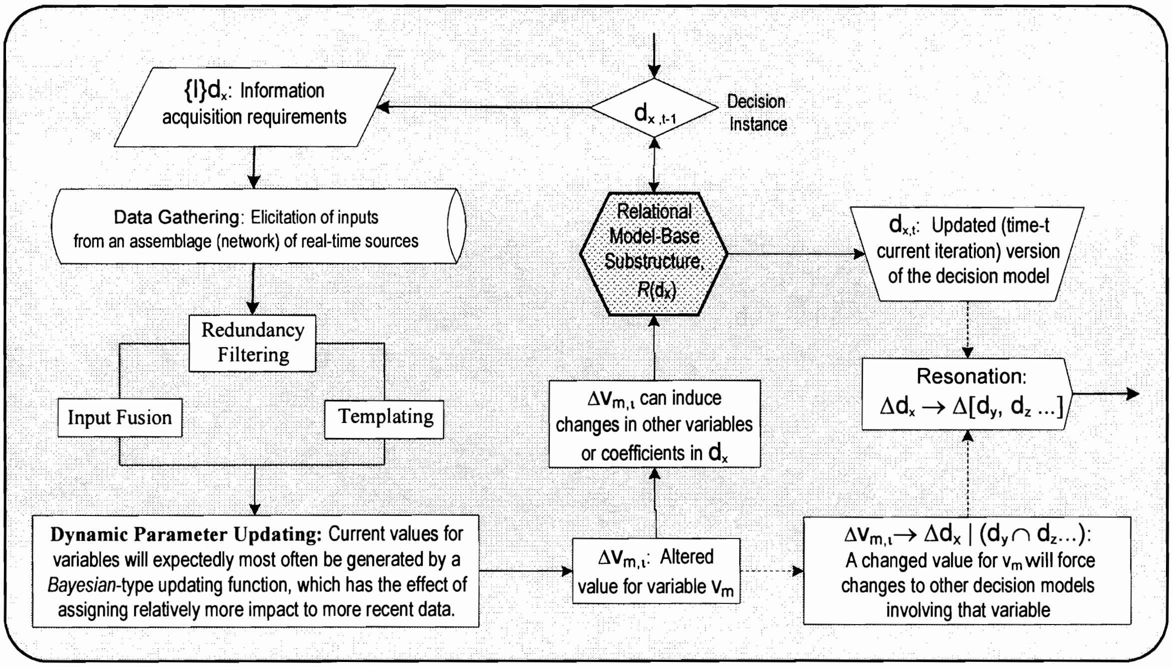

Figure 9: Dynamic Parameter and Model Updating using Bayesian Updating Functions in a Relational Model Base

Non-hierarchical Entity Relationships in Decision Making

With the habitat conservation portion of the relational model-based-centered integrative system detailed for the government entity mediating a conservation group and a corporate interest, an in-depth discussion of the non-hierarchical relationship between the conservation group and the corporate interest can be undertaken. The demands of the conservation group, which are to achieve measurable success in terms of biodiversity and ecological conservation, and the demands of the corporate interest, to maximize profit, are non-hierarchical; in fact, these demands are interdependent. Neither group can achieve its interests without having an effect on the operations of the other. A third-party or other entity would have to be present to mediate the demands of both groups (assuming our present system of democratic capitalism). Yet, for satisfaction of both groups' interdependent interests, the third party entity's relational model-base substructure, in this case that of a government entity, should not solely rely on the inputs and lobbying efforts of each group for information acquisition requirements and for the inherited structural model for conservation. Ideally, there would be some independent way for the government entity to build its relational model-base structure that accurately reflects conservation and development interests without the model inordinately favoring either side's interest. Land management guidelines, monitoring and adaptive management studies, and management guideline revision to inform the government entity's inherited structural model would be the result of testing hypotheses on wildlife habitat and ecosystems and interpreting the results in an objective manner (Morrison et al., 1998). In terms of information acquisition, environmental parameters would need to be identified and realistically monitored in a cost effective way.

As for the inherited structural model, it is important to note that the very concept of what is at risk in ecological economics, one shared by biologists, managers, decision makers, and politicians, varies widely. Fixing the concept of what is "at risk" to the condition of the land, not the status of one's career or the political decision space of management directives, is imperative for interpreting the results of adaptive management in an objective manner. Therefore, when creating a model of which state variables are relevant and how these relevant state variables are interlinked with each other and in what ways, an independent viewpoint must be taken where conflicts can be most objectively resolved, as opposed to cursorily dictated to by strictly subjective interests.

Employees of the conservation group and those of the corporate interest are clearly not members of the same organizational entity, yet in this decision-making case, they do act as laterally-integrated organizational units (through the intermediary of the government entity) that are involved in an intra-task, decision-making relationship, the task of land resource allocation and conservation. The remainder of this section will discuss the non-hierarchical, decision-making relationship between the conservation group and the corporate interest in the relational model-base system context and how the government entity's relational model-base system is involved in the interaction between the two organizational units from the perspective of using relational model-base structures.

The basis of the relationship between the relational model-base structures of a conservation group and a corporate interest starts with the view of their interaction as part of an organization, where $O \rightarrow D \times E$, where D is the set of decision requirements for the task of land/habitat resource allocation, and E is the group of organizational entities within the conservation group's and corporate interest's organizations that would be involved in accomplishing the task. Based on a decision tasking table for a relational model-base structure, Table 13 presents the table for this illustrative example.

Table 13: Decision Tasking Table for Illustrative Ecological Economics Example

	Organizational Entities		
Tasks	**E_1 = representative decision-makers of conservation group**	**E_2 = representative decision-makers of corporate interest**	**E_3 = representative decision-makers of government entity**
K_1 = amount and location of land and to what degree the land is rendered unfit for future uses	D_{11} = list of decisions that the conservation group makes in determining amount and location of land and to what degree the land is rendered unfit for future uses, e.g. which land tracts are key to protect in terms of biodiversity, how much land would we like to see protected, which activities would we like to restrict in riparian buffers and other special ecological zones.	D_{12} = list of decisions that the corporate interest makes in determining amount and location of land and to what degree the land is rendered unfit for future uses, e.g. which land tracts are most profitable to develop, how much land would need to be developed in each tract, do any current land protections make it unprofitable to develop certain property.	D_{13} = list of decisions that the government entity makes in determining ***actual*** amount and location of land for preservation/development and to what degree the land is rendered unfit for future uses ***derived from desired decision models from other organizations,*** i.e. which land tracts are going to be developed, which tracts are going to be preserved, how much land is going to be appropriated to each endeavor, what activities will be restricted in each area?

Referring to Table 13, the decision-tasking table for this case, the organizational entities, E_1 and E_2, would be represented by relevant organizational groups within the conservation group and the corporate interest, such as biologists, habitat managers, land developers, etc., who have a responsibility for decision making related to land/habitat resource allocation. The task, K_1, would involve determining the amount and location of the land and to what degree the land would be rendered unfit for certain future uses. At the intersection of E and K in the decision-tasking table, D represents the list of decision requirements involved in task K_1 assigned to each organizational entity. In this preservation case, $D_{(E1,\ K1)}$ is going to involve the decisions on the land allocation task (K_1) made by the habitat managers and others in the conservation group, where E_1 is the conservation group's habitat managers et al. as an organizational entity. The decision array $D_{(E2,K1)}$ is similar, save it involves decisions made by the corporate interest's land developers (E_2) regarding the land allocation task (K_1). The non-hierarchical relationship between the entities signals that while the ultimate goal of task K_1 is to determine land allocation, each entity is going to represent a different purpose in the land preservation decision model, hence the need for the relational model base and the ultimate decision-making authority on tasks of this nature residing with a third party entity under the tenets of democratic capitalism. This external relational model-base structure would be necessary in any case where the entities had an interdependent relationship with no clear hierarchical structure. It is also important to note that the external organization in which the mediating relational model-base structure is placed will ultimately be of greater authority than either of the entities that are involved in this case; otherwise, no coherent decisions could be made. If a social theory embodying the tenets of welfare economics and utilitarianism were employed in this case, attempting to maximize the level of social welfare (the summation of the welfare of all the individuals in the society) in economic efficiency and income distribution, as opposed to operating under democratic capitalism, this external organization constraint on the mediating relational model-base structure could be removed.

As in the previous case, the entities (E) in the decision-tasking table do not have any direct correspondence with the formal organizational components that appear in organizational charts. Indeed, the entities are not part of the same organization, nor do they necessarily conform to a formal organizational chart within their own organization. In this case, it is necessary to have the entities represent groups of decision-making responsibility, as opposed to representing groups of administrative authority, as neither of these entities have any authority over each other (as reflected in the nature of a non-hierarchical relationship.) It is only by separating the decision-making entities from the formal organizational units in this case of land/habitat preservation and allocation and having the entities from differing organizations participate that the opportunity exists for technical considerations to influence the organizational entity relationships, possibly engaging the administrative and technical apparatus of the external entity, which is informed by these groups, in finding optimum at the margin solutions for habitat management.

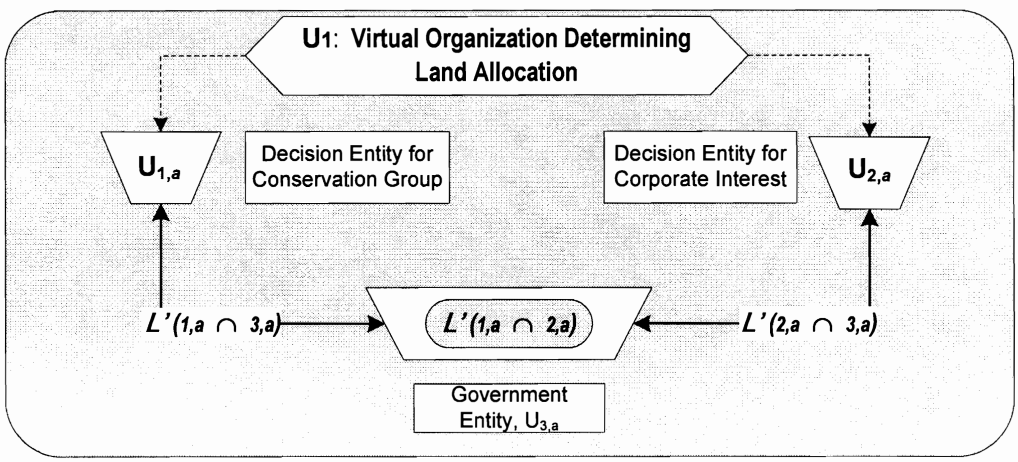

Figure 10: Conventional Organizational Construct for Illustrative Ecological Economics Example

In direct contrast to the hierarchical case, the non-hierarchical case does not increase lateral integrative requirements between the organizational sub-entities of the conservation group and the corporate interest. Instead, it increases the lateral integrative requirements of the two through the external third party (who also has entities involved in decision making). Figure 10 details a conventional organizational construct involving the three organizations in this case: the conservation group (U_1), the corporate interest (U_2) and the government entity (U_3). Assuming that the decision responsibilities for both the conservation group and the corporate interest rest in some department of each organization, the decision entity for the conservation group (U_1) would be $U_{1,a}$, where "a" designates it as the first of undoubtedly several subdivisions of the conservation group's organization, and the decision entity for the corporate interest (U_2) would be $U_{2,a}$, while the decision entity for the government entity (U_3) would be $U_{3,a.}$ The entities are from different organizations, but it is not material, as organizational entities are posited to be peers within this virtual organization and so all of equivalent decision-input authority in this decision-making scenario. It is assumed that the government entity places equal value on the input of all other entities to eliminate bias from the inputs of any of the entities.

Where this case diverges is in how neither of the primary entities (the conservation group and the corporate interest) has the ultimate decision-making authority, only the assumed dispassionate intermediating entity (the government entity) does. It is crucial that each primary entity is laterally integrated with the intermediate entity, although not necessarily directly with each other. Lateral integration exists with each individual primary entity and the intermediate entity, so that the lateral relationships of interest would be $U_{1,a} \leftarrow L'(1,a \cap 3,a) \rightarrow U_{3,a}$, where $L'(1,a \cap 3,a)$ is the highest order lateral linkage connecting the conservation group and the government entity and $L'(2,a \cap 3,a)$ is the highest order lateral linkage connecting the corporate interest and the government entity. Where the relational model-base structure promotes lateral integration in this case is the indirect integration between $U_{1,a}$ and $U_{2,a}$ that occurs within the government entity's relational model-base structure, so that $L'(1,a \cap 2,a)$ actually appears within $U_{3,a}$.

In these linkages, the government entity ($U_{3,a}$) would need access to the models the two external decision-making entities ($U_{1,a}$, $U_{2,a}$) used themselves to determine their position, and not just the output that results in the position of the entity. This transparency takes the government entity's relational model-base structure output from a political compromise solution to a scientific, optimum at the margin solution, which is more objective, enabling the government entity to provide a multi-criteria resolution in terms of trade-off that mediates the axiological model(s) of the conservation group and the rationalization model(s) of the corporate entity. Ideally, the government entity relational model-base structure would incorporate all intersects between the conservation group and the corporate entity for solutions.

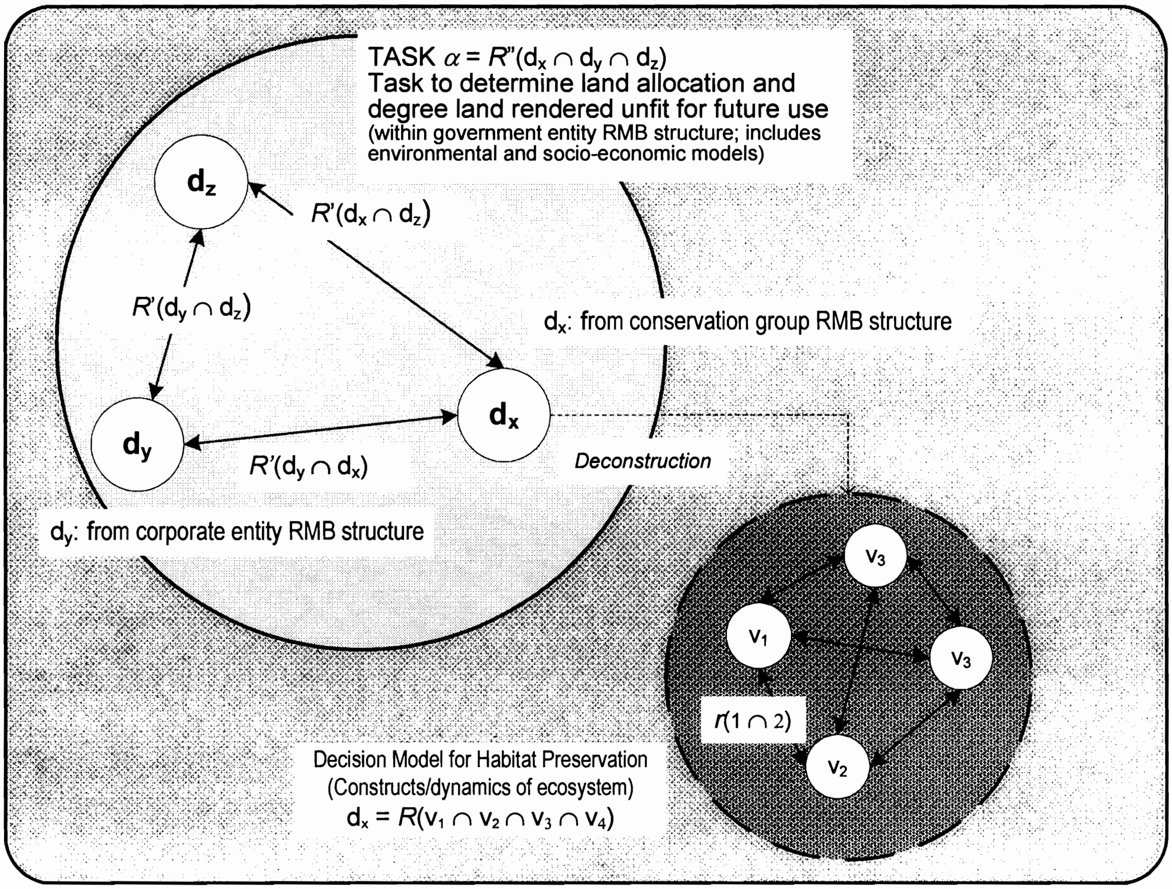

Figure 11: Cellular-Connectionist Relational Model-Base Construct for Illustrative Ecological Economics Example

When considering the task of land allocation, while the relational model-base structure for $R(d_x)$ related to the habitat preservation decision model is complete, it does become necessary to expand the relational model-base structure to include other relational model-base substructures, each one relating to any additional decision model involved in the land allocation task. Referring to Figure 11, the decision model for habitat preservation alone is d_x. In addition to the habitat preservation model (d_x), there is also the commercial value extraction model (d_y), which would use information on real estate market conditions to inform the decision model. The commercial value extraction decision model (d_y) would have its own relational model-base substructure, $R(d_y)$, which would include all of the pertinent variables to the decision of, continuing the example, how much the land that is under consideration for preservation would be worth if it were developed in the interests of the corporate entity.

Habitat preservation decisions (decision model, d_x) are interrelated to the decision model of what to land to develop (d_y), leading to first-order relational operators (R') encoding the intersect conditions between the preservation decisions of a particular tract of land (d_x) and the development decisions of that same tract (d_y), i.e. $R'(d_x \cap d_y)$, the inter-decision relationships. $R(d_x)$ and $R(d_y)$ are outlined in Table 14.

Table 14: Decision Models Involved in Task α and their Substantive Specifications

Decision Model	Substantive Specifications for Model
d_x = the conservation group's decision model for habitat preservation	$R(d_x)$ is $v_1 = v_2 v_4^{v_3}$
d_y = the corporate entity's development decision model for a particular tract of land	$R(d_y)$ is $v_5 = v_4 * v_6$, where v_5 is the total profit derived by development, and v_6 is the marginal profit gained from each parcel of land area

First-order relational operators, i.e. $R'(d_x \cap d_y)$, alternatively expressed $R(d_x) \cap R(d_y)$, would describe intersect conditions among the relating decision models. If these intersect conditions could be described in a mathematical relationship, the R' would become a mathematical expression, F'. In this example, $F'(d_x \cap d_y)$ is that v_4 is the same variable in both models and would have the same value at a given point in time that the relational model-base structure was executed.

All intersections of the first-order relational model-base structures would be held in a second-order relational model base structure, R'', which in this illustrative example, indicate intersect conditions for all decisions comprising the task of allocating land for preservation or development. Thus, when the government entity is brought into this model, second-order relational operators (R'') are involved (intra-task) to comprise the task of determining whether to preserve or develop a tract of land, hereafter referred to as Task α, shown in Table 14. Task α effects connections among the entire group of decision instances comprising this task and link, in this example shown in Figure 11, three first-order relational operators, denoted $R''_{K\alpha} + (R'(d_x \cap d_y) \cap R'(d_y \cap d_z) \cap R'(d_x \cap d_z))$. The intersection in this example consists of v_4 being the same variable represented in both models, signifying the amount of land to be used. In the two models interrelated in Task α, this common variable has the same value in each model. Although in this particular example the intersection only involved one variable, the intersection would also apply to other examples by involving relational operators on all variables that belonged in one of the decision models that also belonged in another relevant decision model to the task, employing the set theory definition of intersection. $R''_{K\alpha}$ could also have a second-order functional counterpart (F'') to effect computational connections among the decisions entailed in a task, most likely involving market exchange clearing functions, even in this simple illustrative example in Figure 11.

In an explication of a more-realistic second-order model with a functional counterpart (F''), Montgomery et. al (1999) has developed a model for pricing biodiversity that includes a chain of multi-criteria, multi-objective models that connect habitat attributes to populations of individual species, populations of species to likelihoods of survival, likelihoods of survival to the benefits associated with biodiversity, and these benefits to the value society places on these benefits, ultimately interconnecting several previously unconnected, application-specific models. This overall pricing model outlines the second-order functional component (F'') of a relational model-base substructure in this domain that houses all of the first-order functional components (F'), such as the species-population survival model and the society biodiversity valuation model. Using this analysis, a relational model-base substructure could be built from the model presented in this Montgomery et. al. paper. An actual relational model-base-type structure that has been built and incorporates several models involved in ecological economics, the object-oriented Integrated Dynamic Landscape Analysis and Modeling System, and its architecture are discussed at length in Chapter 6.

Economic Implications

Land management arguments and resource allocation decisions are made in a cost/benefit context. The economic side of cost/benefit analysis is relatively straightforward only as it relates to market-mediated components or components for which some market good or service is a reasonable proxy. Therefore, for those on the development side of the land management debate, the arguments are easily made; for those on the preservation side, the challenges are formidable to making the argument. In the case of ecological economics, the existence of salient non-market costs and benefits is widely recognized; however, it is difficult to assign valuation to these components. From an ecological perspective, the benefits are decentralized and non-excludable, so the benefits are easily discounted. As is the case with public goods, the market exchange as an intermediary between models cannot be used. Additionally, in the matter of biodiversity, this difficulty in valuation is compounded by ignorance of the ecological relationships on which these costs and benefits depend. Thus, the solutions that presently exist are well-known solutions to the free rider problem associated with public goods: government provision, demonstrated through laws (the Clean Air Act) and international treaties (Kyoto Accord); and non-individualism, appealing to individuals' sensibilities as "global citizens" for solutions to ecological problems. Neither of these strategies is proving to be efficient or effective in providing solutions in the ecological economics domain.

In the economic case of a hierarchical relationship between entities, adopting relational model bases as a technical tool for adopting a real-time approach to organizational decision making is only desirable to the extent that it can be expected to result in a net reduction of the expected value of decision error. This stands in contrast to the case of a non-hierarchical relationship between entities, where the primary attraction is the ability to get real-time, unbiased technical decision data for decision making in matters that involve scenarios where there is no clear overarching interest that either primary entity in the decision can impose upon the decision, thereby allowing the realization of an objective decision outcome that is less subjective than otherwise possible. Within the context of a governmental entity's decision making with respect to habitat conservation and land allocation, providing enhanced real-time information and decision predicates, in addition to incorporating feedback from previous resource allocation decision outcomes in a timely, unbiased manner gives the governmental entity a better decision technology than was available previously. As part of a larger relational model-base-centered integrative system, a relational model-base substructure applied to the decision domain of habitat conservation would provide a sorely-needed technical solution for resolving non-hierarchical entity conflicts of interest in a more rational and unbiased manner.

This is not to say that corporate interests and conservation interests will always remain at odds. In fact, in the opinion of Hawken, a noted environmentalist specializing in the impact of commerce upon the environment, it is likely that these two opposing interests will not be able to remain at odds and ultimately continue to sustain humanity and all other forms of life. To create an enduring society, a system of commerce and production is needed where every act is inherently sustainable and restorative. Business will need to integrate economic, biologic, and human systems to create a sustainable method of commerce (Hawkin, 1993). Additionally, the new system of accounting will have to account for the value of the human and natural forms of capital, which are currently under- or un-accounted for, as well as the financial and manufactured forms of capital (Hawkin, Lovins, & Lovins, 1999). This is already in evidence in the initiatives of one of America's largest corporations, GE, where the corporation is including in its performance incentives, not only the return on investment, but also the depth in cutting its emissions of carbon dioxide ("A Lean, Clean Electric Machine - the Greening of General Electric," 2005). Indeed, understanding that solutions lie in understanding the interconnectedness of problems, and not confronting them from the position of singular entity interest, will lead to initiatives toward enhanced ecological solutions.

Throughout this investigation of a non-hierarchical case, it is instructive to point out the differences between ostensibly non-hierarchical, inter-organizational cases, as they can have very different characteristics depending on the organizational entities involved. If the inter-organizational endeavors only involve corporate interests, or more broadly, organizations whose primary interest is to maximize profit, the "non-hierarchical" case reverts to a hierarchical case, as there will always be one organization in the relationship that will have plenary power over the other(s). The amount of profit and how it is maximized will always favor one corporate interest, the strongest entity in the supply chain, over the other participants. However, generally, if the inter-organizational cases involve an entity of a type other than corporate, such as non-profit or governmental, the non-hierarchical case remains largely intact. No one entity has direct power over another in the scenario, as each entity is approaching the decision-making task with a different goal outcome. Under democratic capitalism, it falls to an intermediate entity with power (legislative, executive or judicial) over the non-hierarchically related others to govern the goal outcome. Although not truly non-hierarchical, as the mediating group does ultimately have power over the others, it remains that the largest stakeholders in the decision outcome do not have power directly over one another, and therefore, this scenario is as close to a non-hierarchical case as this social system will allow to exist. Among societies, if there is going to be resolution to the task of stewardship of the environment globally, there needs to be provisioned a mechanism for international cooperation, where each country is essentially a sovereign entity and the relationship of each country to another is truly non-hierarchical.

The difficulty in explicating a truly non-hierarchical case is that there needs to be a decision authority chosen at some level of the decision-making process, as the economic structure of democratic capitalism stands, indeed in any form of government thus far devised and implemented. Investigation into the problem begs the question of whether there can be a substitute for a decision authority between two non-hierarchically related entities, so that the decision outcome in the non-hierarchical case could be objectively based, as opposed to subjectively based. Based on the present state of social choice theory, and in light of Arrow's impossibility theorem (Arrow, 1970), the answer is no. There is no general way to aggregate preferences without running into some kind of irrationality or unfairness. Yet, if this decision authority could be substituted, it would be a significant advance in terms of resolving problems of ecological economics, among a whole host of non-hierarchical decision-making situations over a range of societal conditions. If there existed a social choice theory where the allocating mechanism is determined based on welfare economics and utilitarianism, attempting to maximize the level of social welfare in economic efficiency and income distribution, relational model bases could be applied within organizations as an allocating construct (model) in the best interest of society overall to enforce objective allocation of public lands, providing a technical solution, as opposed to a strictly socio-economic solution. Instead of a mediating governmental entity, a mediating model or set of models residing in a relational model base would establish the conditions or basis of interdependent solutions.

Any attempt to better inform land management and preservation decisions, even at a local level, is beneficial. One of the substantial contributions of this case is that any attempt at developing a credible decision technology for ecological interests, including the application of relational model-base structures, might eventually contribute to an information system that can be reliably brought to bear in answering these questions of ecological cost/benefit considering biodiversity as a counter to the development arguments in land management decisions. Another interesting application of relational model-base structures would be to apply them for dynamic policy formulation, as an analogy to dynamic resource allocation. This would allow for the discovery-based approach to policy through action research, providing freedom from the fixed weighting of decision choices, as opposed to a policy commitment that would have to be made early then revised over a long time period post-failure. Overall, this approach would increase the real-time information capabilities of the entities responsible for environmental stewardship.

It should be a goal of information systems researchers, in addition to decision scientists and management scientists, to instrument technical solutions to solve problems such as those of responsible land resource management, as optimally as possible in light of the social and economic constraints under which society operates. More research along the lines of relational model-base structures applied to decision making in ecological economics will contribute to the development of information and decision technologies that can encourage more objective, rational global solutions to problems that are currently solved through purely subjective treatment, dealt with only locally, or left all together unaddressed.

CHAPTER 6 Implementation of a Type 5 or 6 Relational Model Base

Perhaps the strongest argument for the theory of relational model bases is their tendency to occur naturally as enterprise decision-making information systems. In organizations where a premium is placed on real-time decision predicates and near-instantaneous decision execution, instantiations of relational model-base structures would serve to provide these organizations with a mechanism to analyze the decision predicates in real time, based on the relevant inherited structural models built into the relational model-base device.

This chapter discusses in-depth the possible implementation of a Type 5 or Type 6 relational model-base system. The first section will discuss the current methods and systems that organizations use to get real-time, integrated decision-making information. There are many types of technology in enterprises today that serve as alternate ways for organizations to acquire real-time decision-making information, pointing out the need for such information systems. One particular technology, OLAP, will be analyzed as it serves as the first, closest attempt to build a relational model base-like system. The second section will outline what the characteristics of an ideal relational model-base implementation would be from a theoretical perspective, including a diagram and architectural information. How the key characteristics of good data systems are incorporated into building a relational model-base implementation will also be discussed in this section. The third and final section of this chapter will discuss two specific relational model-base systems, the Insight Precision Farming System with an AgriDNA Input database (http://www.123farmworks.com/insight.htm) and the object-oriented Integrated Dynamic Landscape Analysis and Modeling System (OO-IDLAMS) (http://www.dis.anl.gov/idlams/), including a model of each of the systems and its architecture. These instantiations of relational model-base systems have been built as a response to enterprise information system demands and provide insight into the benefits and drawbacks of these attempts at building a relational model base. The contrast between these relational model-base systems, of which Insight and OO-IDLAMS are examples, and the characteristics of an ideal relational model base will also be discussed.

Current Methods and Systems

In beginning a discussion on relational model-base instantiations, it is worthwhile to discuss the types of information systems organizations currently use to get real-time, integrated decision-making information. Most of these are applications of business intelligence techniques. One example is predictive analytics, which enhances an organization's decision making by applying sophisticated analysis techniques to enterprise data. From a technical perspective, it is the branch of data mining concerned with the prediction of future probabilities and trends. Enterprise systems that are based on predictive analytics used for decision making incorporate predictive technology to augment the planning and decision-making process. Often, predictive analytics was built into business performance management (BPM) products that progressed beyond traditional business intelligence to offer in-depth and unified information on managing and controlling organizational and individual performance. BPM products give organizations insight into their operations in real time by monitoring business processes and sifting through event data and metrics spawned by those processes to track important trends and detect anomalies. These BPM products have three essential components: event monitors; filtering and analysis engines; and notification/alert systems. The goal is to provide real-time access to critical business performance indicators to improve the speed and effectiveness of business operations (Hayes, 2005). These analysis methods enable enterprise data that cannot be easily manipulated within the relational database to be extracted and analyzed to be able to predict future operational performance.

Another type of enterprise information system that provides organizations with real-time, decision-making capabilities are incorporated into intelligent process automation. As another advanced business intelligence technique, intelligent process automation (IPA), deployed through operational business intelligence software, delivers key capabilities for dealing with real-time data integration in operations/production analytic applications by automating recurring or repeatable decision-making processes that exist in the environment (Vesset, 2005). More than providing organizations with strictly decision-making information, IPA seeks to replace human decision makers with automated decision processes to be able to take advantage of the real-time information that can more easily be processed by machines rather than man. This particular type of enterprise decision-making technology provides real-time decision processes through disintermediation of the human decision maker, as opposed to faster processing of data mined from databases and analyzed for trends and decision relationships, as predictive analytics and BPM do. From the perspective of organizational integration, none of these systems mentioned above provide a significant enhancement, as the decision-making entities within the organization are not necessarily required to align more closely to implement these data mining and business intelligence techniques.

Another approach to real-time integrated decision making which does not rely on business intelligence techniques is that of stream processing. Stream processing is used in a complimentary fashion with relational database management systems to provide real-time information to decision makers. A stream-processing engine grabs incoming data and analyzes it as the data passes by. Engines use an inbound query processing model, in which records are processed before they are indexed and stored. Records flow through the query, which can transform data while it is moving *before* it is stored. This stream processing engine can filter structured or unstructured data and decide immediately which should be presented to an analyst at once, which can be stored for later queries and which can be discarded (Anthes, 2006). The ability of the stream-processing engine to provide real-time information is not an advantage based on an improved architecture; it is an advantage based on the stream-processing engine being resident in the RAM of the larger database system. Therefore, current implementations of this stream-processing engine do indeed provide more current information for decision making, as is the goal of relational model-base structures. In contrast, relational model bases provide more current information based on an enhanced model-based architecture, as opposed to merely relying on faster processing power and larger RAM for analytics on a data-based architecture.

Online analytical processing (OLAP) arguably serves as the first attempt at building a relational model base-like system. While still using a data-based system, databases configured for OLAP employ a multidimensional data model, combining data from a multitude of data sources (Codd, Codd, & Salley, 1993), similar to that to be achieved with a relational model-base structure. This structure enables complex analytical queries with a rapid execution time, giving decision makers vital information in real time. OLAP cubes are the basis for this analytical ability, with the cube consisting of the calculation of the relational data aggregations and the base data (Pedersen & Jensen, 2001).

The primary difference between OLAP and a relational model-base system lies in how models are specified in each of the systems. In OLAP, the OLAP cube is created from a star schema of tables, with a fact table and numerous dimension tables linked to the fact table. OLAP cubes can also be created from a snowflake schema or a starflake schema. Snowflake schemas normalize dimensions to eliminate redundancy, so the dimension data has been grouped into multiple tables, instead of one large table. This is a variant of the star schema where each dimension can have its own dimensions. Starflake schemas are hybrid structures that contain a mixture of (denormalized) star and (normalized) snowflake schemas. These tables show how the aggregations of relational data can be analyzed. Due to the potentially large number of aggregations to be calculated (ultimately determined by every possible manner in which the original data can be hierarchically linked), often only a predetermined number are fully calculated, while the remainder are solved on demand. Whereas the OLAP cube structure is based on the data and the calculation of the relational data aggregations, relational model-base substructures are based on an inherited structural model describing the decision-making scenario. With OLAP, model specification updating is difficult, meaning OLAP does not provide the flexible architecture necessary as described in the relational model-base scenario. With a relational model-base structure, the inherited structural model is going to be derived from situational variables and constraints on algorithmic relationships among the variables prior to the data processing occurring, not strictly from aggregations of the data collected in the data warehouse as OLAP models are. This allows for the relational model-base structure to have an advantage over OLAP in that external data sources can be used as inputs in the information acquisition stage of the relational model-base system, in addition to any information native to data sources in the organization. Also, OLAP does not necessarily function in real time, as relational model bases do. Nevertheless, OLAP does provide a significant first step towards building a relational model-base substructure system.

Another challenge in building relational model-base systems comes in determining how the model is to be modified, or in the case where many models are present, how a particular model is to be selected. In the case of OLAP, all possible aggregations are present and able to be calculated, so this idea of model selection is not directly addressed. OLAP is trying to support a representation (cube) that can be useful for many decision models. Yet, a distinct advantage of the relational model-base system is the updating system that serves to feed new parameter information to the relational model-base substructure, as well as specifies any changes in the relationship among the variables. The updating system would then be able to direct any model modifications or choose which model is appropriate when a selection of models is available.

Implementation of an Ideal Relational Model Base and its Characteristics

Arguably, implementations of the best possible relational model bases would be systems based on decision models using true objects and symbolic programming. As originally conceived utilizing these tools, there are no relational model-base system instantiations. However, latest generation programming languages can represent objects and describe object behavior, not just describe the characteristics of the object, meaning that it is possible to build a relational model-base substructure technically without much compromise being made that resulted from the tools being used to build the system. An example of a relational model-base model is shown in Figure 12.

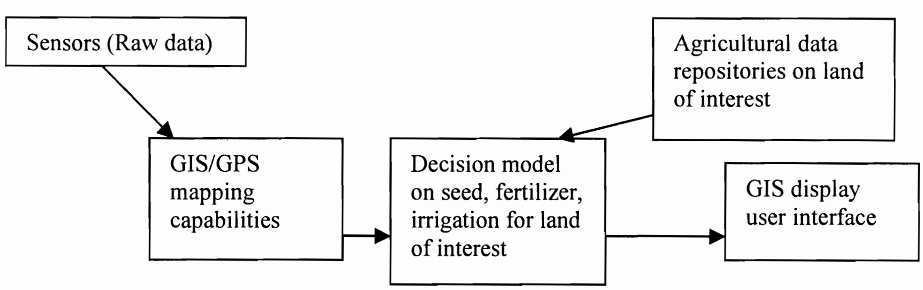

Figure 12: A Relational Model Base Model

The quality of an object-oriented architecture can be described by a set of characteristics: modularity; extensibility; flexibility; adaptability; understandability; testability; and usability, in addition to reliability and efficiency, which are recognized to facilitate the evolution and the maintenance of software systems (Boehm et al., 1978;

Borne, Prieto, Brito e Abreu, & De Meuter, 1998; Nguyen-Tuong, Chapin, Grimshaw, & Viles, 1998). Each of these characteristics of an ideal relational model-base system will be outlined and discussed in this section.

Modularity in a system is defined as the ability to build the system out of simple modules connected by well-defined interfaces, so that most problems are local. This ensures the ability to fix or optimize a portion of the system without breaking the whole system (Raymond, 2003). Relational model bases are designed as modules, with the sensor data and other data acquisition processing, the decision model, and the GIS display or other graphical user interface all being coded separately. The inherent modularity makes it possible to troubleshoot or debug any of the individual modules that make up the relational model base without interfering or possibly damaging others. This attribute is essential for the ability to alter input data analysis procedures as sensors and GIS processing become more sophisticated in addition to altering graphical user interfaces for enhanced output, necessitating module replacement for handling those inputs and outputs to the system.

Extensibility is defined as the ability to extend the functionality of a system within a consistent framework, so that later developers can extend the system's capabilities (Nguyen-Tuong et al., 1998). A relational model-base system would have to be extensible to allow for additional sensors to be added to the system or any other data acquisition inputs that would have an impact on the parameters or inherited structure of the decision model. Additional graphical user interface displays could also be generated for decision making, requiring extensibility of the relational model-base system to accommodate the requests. The relational model-base examples that are discussed later in the chapter are extensible, allowing for additional sensors, data acquisition input mechanisms and output displays to be used should the decision-making organization require them.

Flexibility is the ease with which a system or component can be modified for use in applications or environments other than those for which it was specifically designed (Institute of Electrical and Electronics Engineers, 1990), also referred to as portability (Boehm et al., 1978). The modules that are used to process the agricultural or ecological data repositories would need to be flexible in that a particular dataset analysis module would be used in other relational model-base structures as inputs to other decision models. Other aspects of a relational model-base system, including sensor software and output display modules, would also have to be flexible if they were to be used in other relational model bases.

Adaptability, or modifiability, is the degree to which a system or component facilitates the incorporation of changes, once the nature of the desired change has been determined (Boehm et al., 1978; M. W. Evans & Marciniak, 1987). The ability of a system to reliably function in the organizational environment and change as new operating requirements emerge is essential to the capability of a relational model-base system to provide real-time, decision-making information. The decision model will have to be updated or substituted as changing conditions or constraints force changes in both the connective specifications and the substantive (determinant-level) specifications of the inherited structural model of the relational model-base substructure. Perhaps the key challenge in relational model-base system development is maintaining sufficient adaptability so that the relational model base can provide quality decision predicates in real time.

Understandability is the ability to understand the program source and the degree to which the purpose of the system or component is clear to the evaluator (Boehm et al., 1978). Each relational model-base instantiation would have to be understandable to be widely adopted, as the business rules and models that underlie the relational model base would have to be readily accessible to developers for rapid modification and to updating functions for modifying models. Undoubtedly, good system development practices of documentation would also be important to achieve an understandable relational model-base substructure that would be functional over time.

Testability is the degree to which a system or component facilitates the establishment of test criteria and the performance of tests to determine whether those criteria have been met (Institute of Electrical and Electronics Engineers, 1990). Rigorous testing of an relational model-base instantiation would be a necessity, as it is with all enterprise software used in production environments, especially those which provide real-time decision predicate information. Each module of the system, as well as the functionality at the interfaces of those modules, would have to pass the appropriate test criteria to ensure that, in addition to enhancing system reliability and efficiency, the data analysis would also be performed properly based on the models and data inputs.

Usability, called human engineering by Boehm et al. (1978), is the extent to which a software product fulfills its purpose without wasting users' time and energy or degrading their morale. While it is unlikely that it would ever be the system developers' conscious intent to create a system that negatively impacts its users, there are several examples of systems that were usability failures (Koppel et al., 2005; Nielsen, 2005). Relational model bases are designed to provide decision support technology to organizations and, as such, should excel in their output usability characteristics. GIS or other graphical user interface displays of the pertinent decision-making criteria to end users are the most critical usability aspect of a relational model-base system, with the ability to move between different visual displays easily being essential. As an example in the agricultural domain, on one GIS display, a user might see a map of the planting site detailing soil composition, then the user might need to quickly toggle to the GIS display of that same area, this time with an overlay of yield information. In the agricultural domain, being able to quickly move between GIS displays enhances the usability and utility of the relational model base as a decision support technology.

The final two aspects of quality system software outlined by Boehm et al. (1978) that are characteristics of an ideal relational model-base system are reliability and efficiency, which are inherent characteristics of any production environment software system. The nature of a relational model-base system in providing real-time, decision-making information would demand extraordinary reliability and efficiency in its environment. Ultimately, it would fall to the judgment of the relational model base's users, the organizational decision makers, to determine if the system met acceptable standards of reliability and efficiency.

With the nine essential characteristics that would need to be incorporated into an ideal relational model-base system defined and outlined, instances of relational model bases that have already been deployed can be analyzed to see if they meet these criteria. There are two instances in particular that are going to be investigated in the remainder of this chapter, one within the domain of precision agriculture and the other from ecological preservation. Table 15 shows the nine characteristics of an ideal relational model-base system and outlines how these two specific relational model-base structures that have already been built meet or, in some instances, fail to meet these criteria. That these instantiations have been shown to function exceptionally well in providing real-time, integrated data in the operational environments in which they are deployed is proof of the concept of relational model-base structures as decision support technology.

Table 15: Attributes for an ideal relational model-base structure and two instantiations of relational model-base structures

	Models		
Attributes	Characteristics of an ideal relational model-base system (definitions)	AgLeader Insight	OO-IDLAMS
Modularity	Can be built out of simple modules connected by well-defined interfaces	Yes – can interchange modules, sensors, and inputs	Yes – executes external model modules in native language through "wrapping"
Extensibility	Can extend functionality of system within a consistent framework	Yes – can add additional modules and inputs	Yes – can add modules to interact in overall model framework
Flexibility	Can easily modify system component for use in other systems	**Difficult to assess, as it is a proprietary system**	**No – only underlying framework (DIAS) is flexible**
Adaptability	Can facilitate the incorporation of changes once nature of changes has been determined	Yes – can incorporate new planting models	Yes – allows modular modifications to models
Understandability	Can understand program source code and degree to which purpose of component is clear to the evaluator	**No – proprietary**	Yes – written in open source and well-documented, as are components
Testability	Can facilitate the establishment of test criteria and performance of tests	**No – proprietary**	Yes – written in open-source and well –documented
Usability	Can fulfill purpose of software without wasting users time and energy or degrading their morale	**Yes – has easy GIS input and output mechanisms to system**	Yes – GUI and GeoViewer for very specialized and well-trained users
Reliability	Can perform intended function consistently in production	Yes	Yes
Efficiency	Can perform intended function parsimoniously in production	Yes	Yes

Examples of Relational Model Base Instantiations

The Ag Leader Insight Precision Farming System

The first example of such an relational model-base structure is the Ag Leader Insight Precision Farming system with the AgriDNA Inputs database. The precision farming information system uses a color touch screen display to allow a farmer to view real-time information as the farmer moves through the planting field. Insight provides controls to a sprayer to allow for manual or variable rate application of seed, fertilizer or pesticide, depending on where the farmer is in the field. The system also generates real-time variable rate application maps, giving farmers immediate, salient information on how much seed, fertilizer or irrigation to place on a field to maximize yield. In fact, this system allows for simultaneous processing of all raw data on field conditions that cause yield differences.

From an architectural perspective, Insight uses controller area network (CAN) bus technology. This allows the Insight console to serve as the user interface for a simple, modular system where a single high-speed cable (a bus) distributes large amounts of information to and from the other control modules, i.e. grain flow sensors, moisture sensors, speed and position sensors, auto steer sensors, application rate modules, etc. A graphic of the architecture of Insight is shown in Figure 13.

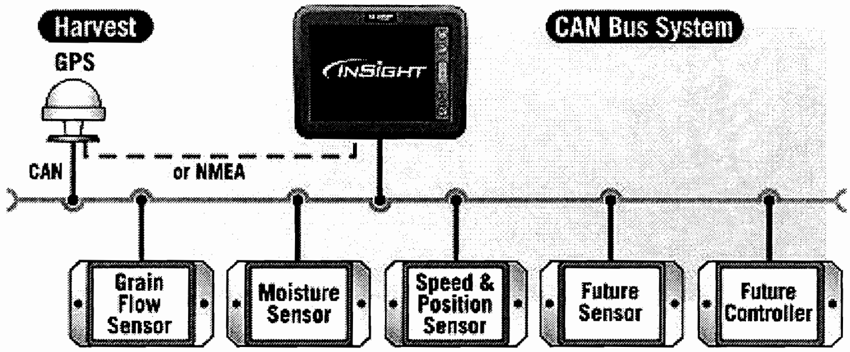

Figure 13: Architecture of Insight, a relational model-base system implementation (http://www.123farmworks.com/insight)

Initial data inputs to the Insight system about field location come from a GPS system directly attached to the controller bus, and additional historical crop and field data is wirelessly transmitted to the console where the data is processed through decision models to be able to direct the application of seed, irrigation, and fertilizer in conjunction with real-time readings from the sensors. The AgriDNA Inputs database provides farmers with standardized data to download on chemical, seed, fertilizer, and general production practice information straight into GPS/GIS software. This database service aggregates real-time updated information on production parameters that are essential for farmers to maximize yield. Embedded within the hardware of the Insight console is the software that specifies the inherited structural model of planting grain, which consists of all of the algorithmic relationships between variables relevant to the planting decision model, such as amount of seed, stage of growth, amount and placement of irrigation and fertilizer, among others. This architectural decision to embed the decision-making models in the hardware allows for an increased responsiveness of the system to the production environment. This provides near real-time execution of the desired actions based on the inputs to the system, enhancing the justification of the decision support system for use in real-time decision making.

The Insight system provides for the nine attributes of a quality object-oriented architecture, although some of the attributes are difficult to assess in terms of the extent to which the attribute is present. By design, the Insight system is modular and extensible. All of the control modules for the Insight system, such as the grain flow sensors, moisture sensors, application rate modules, etc., are connected by the controller bus, with the Insight module itself acting as the user interface. Each of the modules is linked through interfaces that allow for it to be easily removed from the system without compromising the whole. This modularity of system components also provides the Insight system with its extensibility. The addition of another sensor module, another module for auto-steering the equipment (AgGPS Autopilot™), or an automatic sprayer controller (DirectCommand), would only involve programming an individual interface for the module within the controller bus framework, and there would be no concern of destroying the capability of the other modules within the system. The on-going utility of a relational model-base system, such as the Insight system, rests on its extensibility to allow for additional information acquisition modules to be added as the model (or models) upon which the system is based are modified or updated, as well as to allow for additional user interface display modules, e.g., more detailed GIS yield and application displays.

It is difficult to judge the flexibility of the Insight system. The entire system is based on a standard controller bus technology, which enhances potential flexibility of the modules and their reuse in other systems. Each of the modules, in particular the sensor modules, could be reused in a system similar to the Insight. As this is a commercial, proprietary software product, the company that owns and develops the system (Ag Leader Technology) would almost certainly want to use modules of the Insight system in other precision farming systems that they create for the marketplace, even though these modules would not be available to the developers of other systems that could potentially use them.

The adaptability of the Insight system is crucial for its being able to incorporate new models into its control system. When the farmer chooses new seeds to plant (which would require different mixes and amounts of fertilizer and modified irrigation) or to plant a different plot of land, the primary model used by the Insight system would be changed to reflect the changed decision model. The Insight system is programmed to allow the farmer to choose which seeds are going to be planted, or what parts of the field are going to be fertilized or tilled, then the system immediately updates the model and begins to create maps and perform the fieldwork based on model outputs. Because most of the optimal planting and tending models are known for common agricultural crops for previously farmed areas, the precision agriculture models that are resident in the Insight system are well defined. With multiple well-defined models resident in the system, the adaptability of the Insight system rests in its ability to easily move among these models as prompted by the farmer based on varying planting scenarios.

Properly assessing the understandability and testability of the proprietary Insight system is difficult. Without access to the source code, there is no way to know if the code is understandable or not. It is assumed that the Insight system is testable; otherwise, it would not be a highly recommended commercial system. Conventional wisdom would dictate that these two attributes are present in the commercial system, yet could stand to be improved. One of the Insight system's greatest strengths lies in its usability. Precision agriculture requires a system that demands little training and provides clear, concise, real-time information to the farmers that are using it. The end-user console of the Insight system is able to display real-time, color maps to immediately show the variability of the farm land. The system's touch screen details real-time color yield and moisture maps, planting maps, and application maps instantly, with map layering capabilities; for example, to show overlays of planting and harvesting maps. The ease of use and real-time information provided by the Insight system maps are a significant improvement over those historically projected yield maps and planting information that are given by industry sales people to the farmers. Ultimately, this improvement translates into profits for the farmer at harvest time. The reliability and efficiency of the Insight system are demonstrated by its commercial viability and the improved real-time, decision-making information it brings to the farmers that use it.

The limitations in quality that exist for the Insight system as a relational model-base system manifest themselves in the inability of the system to be as flexible, understandable or testable as it might be. That Insight is strictly a precision farming application does lead to its modules being less flexible than desired. While it is difficult to assess the understandability and testability of a proprietary product, it is likely that inspection of the Insight system code would find areas of improvement for these two aspects of the system. Overall, Insight is a good example of a relational model-base instantiation already deployed in a production environment.

Another important aspect of relational model-base systems is the ability to handle decision model specification. The technical capability of an ideal relational model-base system with relation to model specification includes the ability to easily represent models, communicate updated parameters, communicate among models, incorporate new decision models, and modify or eliminate existing decision models. Table 16 shows the capability of an ideal relational model-base system in contrast to the abilities of the two example relational model-base systems. The Insight system is primitive in its model specification abilities. It does easily represent models as embedded software. The end user prompts communication among models, and agents within the embedded software communicate updated parameters. Where Insight falls short in the technical capabilities of an ideal relational model-base system is in adding, modifying or deleting decision models. Whereas an ideal system would be able to dynamically and autonomously perform these functions, Insight requires static, vendor-provided updates to be manually installed to add, modify or delete a decision model.

Table 16: Attributes for an ideal relational model-base structure and two instantiations of relational model-base structures

	Models		
Technical Capabilities	Characteristics of an ideal relational model-base system (definitions)	AgLeader Insight	OO-IDLAMS
Easily represents models	Yes	Yes	Yes
Communication among models	Yes, prompted by decision authority	Yes, prompted by end user	Yes, prompted by end user
Communication of parameters	Agent-based	Agent-based	Agent-based
Easily incorporates new decision models	Yes, dynamically through agents scripting changes with learning involved	Yes, through static, vendor-provided updates; no learning involved	No, manually added by programmers
Easily modifies or eliminates decision models	Yes, dynamically through agents scripting changes with learning involved	Yes, through static, vendor-provided updates; no learning involved	No, manually added by programmers

The Integrated Dynamic Landscape Analysis and Modeling System (IDLAMS)

Argonne National Laboratory's Integrated Dynamic Landscape Analysis and Modeling System (IDLAMS) integrates data, environmental models, land-use planning, and decision support technologies within a GIS-based or object-oriented-based framework. Originally developed for military use, IDLAMS consists of ecological, terrain and erosion models, along with advanced decision support technologies, all linked with a core vegetation model that uses GIS, remote sensing, and field inventory data. The key benefit of IDLAMS is that it can help resource managers in three important ways: (1) to identify multiple land use objectives and incorporate trade-off analysis; (2) to determine the cost and economics of viable alternatives for managing land use; and (3) to incorporate "what if" scenarios into decision-making. IDLAMS can also speed up responses to land-use management issues, improve environmental compliance, and reduce conflicts between competing land uses (Shoemaker, Dai, & Koenig, 2005). Overall, the object-oriented IDLAMS provides environmental managers and decision makers with an adaptive approach to integrated natural resources planning and ecosystem management (Sydelko, Hlohowskyj, Majerus, Christiansen, & Dolph, 2001; Sydelko, Majerus, Dolph, & Taxon, 2000).

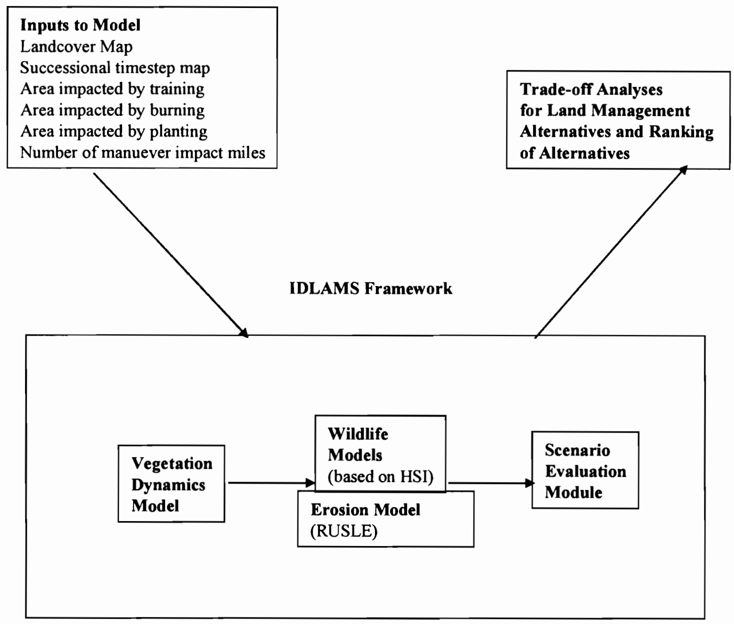

Figure 14: Architecture of IDLAMS, a relational model-base system implementation

A graphic of the IDLAMS framework is shown in Figure 14. Four major models were developed and integrated for the IDLAMS prototype: (1) a vegetation dynamics model; (2) a set of wildlife habitat suitability models; (3) an erosion model; and (4) a scenario evaluation module. The Vegetation Dynamics Model is the core model for IDLAMS because the output from this model is the input for all other connected IDLAMS models. The Vegetation Dynamics Model is a spatially explicit model that incorporates vegetation changes due to (1) natural succession, (2) land use impacts, and (3) land management actions. The Wildlife Models are five sub-models that represent individual wildlife species and are based on U.S. Fish and Wildlife Service Habitat Suitability Indices (HSIs). Each sub-model requires that the user input either a vegetation/landcover map representing the current condition or a simulated landcover map generated by the

Vegetation Dynamics Model. The framework integrates RUSLE (the Revised Universal Soil Loss Equation) into the erosion model to generate an erosion status map for each current condition or simulated vegetation/landcover map input by the user. The scenario evaluation model uses a value-based, decision-analysis process to link the ecological models with the management needs and user requirements of the resource manager. The model inputs are the landcover map, a successional timestep map of the area, the area impacted by training (land use), the area impacted by burning, the area impacted by planting, the number of maneuver impact miles and RUSLE parameter values. Once modeled, the scenario evaluation module is used to perform trade-off analyses for land management alternatives, on the basis of the results from the spatially explicit modeling, and to rank the alternatives according to how well they meet the specified objectives.

Underlying OO-IDLAMS is an object-oriented architecture called the Dynamic Information Architecture System (DIAS). DIAS supports the distributed, dynamic representation of interlinked environmental processes and behaviors. For integrated environmental modeling, the main components of a DIAS simulation are: (1) software objects (entity objects) that represent real-world entities, such as atmosphere, fish, or groundwater; and (2) simulation models or other applications that express the dynamic behaviors of the real-world entities (e.g., surface exchange, reproductive cycles, and fate and transport). In DIAS simulations, external models or applications participate in a simulation through a formalized registration process that "wraps" each model or application for use in DIAS. This "wrapping" process requires a formal registration procedure that enables the DIAS entity objects to implement external models to address behaviors. The "wrapped" models and applications run in their native languages rather than requiring translation to a common or standard system language.

The advantages of this model are derived from its object-oriented nature. The object-oriented approach overcomes several limitations of a GIS-based integration framework, which is static in nature and does not lend itself to dynamic inter-model processing. In terms of modularity, OO-IDLAMS can execute external applications in their native language (e.g. FORTRAN or C) and allows them to dynamically interact with each other indirectly via those real-world ecosystem objects that package attribute information together with behavior (how the object acts and reacts). Therefore, each module of the OO-IDLAMS can be individually modified without affecting the whole system or any of the individual model components. Because external applications do not interact directly with one another, OO-IDLAMS provides an extensible environment that easily accommodates adding and removing applications of models.

While OO-IDLAMS itself is not very flexible, the framework upon which it is built, DIAS, is extremely flexible and has been applied to other domains where multiple model integration is beneficial, including healthcare (the Healthcare Management Simulator) and oceanography (the Integrated Ocean Software architecture). DIAS can be customized to suit any scenario where multiple model integration is called for, with the limitation that substantial skills in programming and in the application domain are needed for full technical utilization of the system (customization). Adaptability is the key advantage of OO-IDLAMS over its predecessor, GIS-IDLAMS. Integration of new environmental models or data formats into a GIS-based framework can require timeconsuming and expensive reworking of the system, while the OO-IDLAMS model allows for modifications to be made in a much more streamlined way. OO-IDLAMS is very understandable, so while complex in its workings, the code is well-documented to allow those with the appropriate expertise to compose and integrate models into the framework and test those integrations.

The OO-IDLAMS system includes a graphical user interface for selecting appropriate applications and for easy data and parameter input. The system's usability is enhanced by an object-oriented GIS called GeoViewer, and in addition, external GIS software applications can be integrated to provide further types of spatial analysis. The primary users of the current OO-IDLAMS are military land managers and decision makers with the U.S. Army Construction Engineering Research Laboratories who are specifically trained to use this system. As additional government and private industry landowners become interested in further developing and using this tool, significant improvements to usability will have to be made to make the system more accessible to a broader range of users.

Although OO-IDLAMS and the underlying DIAS provide an excellent framework for the integration of multiple models, it does not solve the more basic ecological and environmental research issues related to model integration. These issues include, but are not limited to: (1) the ecological implications of multiple-scale modeling and simulation; and (2) the impacts of data aggregation and disaggregations. However, DIAS can be used as an excellent framework from which to explore and investigate these issues. In addition, further development of the DIAS architecture should include the application of uncertainty analysis functionality to models within the DIAS suite.

Like the Insight system, IDLAMS is very primitive in its model specification capabilities. IDLAMS does easily represent models, as it incorporates already built models in their native language into its framework through an interface "wrapper." The end users (military/government analysts) prompt communication among models, and agents within the framework communicate updated parameters among the models. IDLAMS, even through built on a very flexible framework, is not able to incorporate new decision models, modify or eliminate decision models very well. Each model modification has to be performed manually by programmers who have specialized training, both in programming and in the application domain of the model. Further development of IDLAMS for wider usage would require significant improvement in the model modification capabilities of the system.

With the two examples of relational model-base instantiations discussed above, it is clear that relational model bases are already occurring naturally and evolving in areas where the integration of multiple models is necessary to provide real-time, integrated information for organizational decision making. The theoretical underpinnings outlined in Chapter 3 and applied in cases in Chapters 4 and 5 can now be seen already developed and working in production environments. This is additional impetus to continue to explore these systems and determine how they can be improved upon in the future.

CHAPTER 7 Discussion and Future Research

Discussion

In the cases discussed in this dissertation, it was shown how relational model-base structures facilitate more accurate, real-time decision making within and among organizations while simultaneously providing a framework for enhanced lateral integration in relationships among organizational entities responsible for decision making. As more tactical and operational situations within organizations appear that have high computational requirements and the strict demand for decision predicates in real time, such as the scenarios in the two cases presented in this dissertation, there will be a more urgent need for effective organizational decision technologies that can accommodate these decision-making situations.

While in the two cases that were presented and the two example instantiations analyzed relational model-base structures were used in a capacity as passive decision aids to a manager, increasingly relational model-base structures will be configured to serve as active decision aids invested with decision-making authority over certain operational tasks, moving relational model-base structures from the realm of business intelligence to that of artificial intelligence. This movement will capitalize on the relational model-base structure's ability to handle routine, regular decisions that submit to a conventional, algorithmic solution, while addressing tasks that are prime candidates to be assumed by greater autonomic computer management functionality, particularly those with heavy computational requirements and strict timeliness or response-related requirements.

In the case presented in agriculture e-commerce, an illustrative relational model-base structure model was developed to show how using a relational model-base system within the hierarchical relationship between the grain miller and grain producer could provide the grain producer with enhanced real-time decision predicate information and introduce more lateral integration with the grain miller to ultimately reduce the expected value of decision error, thereby improving the profit margins for the grain producer over a scenario without the improved information base that the relational model-base structure provides. This was expanded upon to demonstrate how multiple decision models, resident within the grain producer's and grain miller's organizations, could be integrated to form a more expansive relational model-base system which would improve operational decision predicate quality for both organizations. The hierarchical nature of the relationship between the two entities in this case dictates that the grain producer's decision processes are constrained by the decision processes of the grain miller. It follows that the grain producer is risk averse, only wanting to produce the exact amount contracted with the miller. Again, the economic benefit of a relational model-base structure in a hierarchical case, such as that presented for the grain producer, is in the improved information base provided by the relational model-base structure which reduces the expected value of decision error.

In the case presented in ecological economics, an illustrative relational model-base structure model was developed to show how using a relational model-base system within the non-hierarchical relationship between a conservation group and a corporate interest, mediated by a government entity, could provide the government entity with enhanced real-time decision predicate information less biased by the inputs from either the conservation group or the corporate interest, in addition to enhancing the lateral integration of both parties to the government entity. The relational model-base structure's primary benefit in this scenario is the ability to get real-time, unbiased technical decision predicate data in matters where there is no clear overarching interest that either primary entity in the decision can impose upon the decision, thereby allowing the realization of an objective decision outcome that is less subjective than otherwise possible. The relational model-base structure would provide a much needed technical solution for resolving non-hierarchical entity conflicts of interest in a more rational and unbiased manner.

The tendency of the relational model-base structure to occur naturally as an enterprise decision-making information system strengthens the argument for developing the theory of relational model-base systems. In organizations where a premium is placed on real-time decision predicates, and if the model itself has decision-making authority, on near-instantaneous decision execution, instantiations of relational model-base structures would provide these organizations with a mechanism to analyze the decision predicates in real time, based on the relevant inherited structural models built into the relational model-base device. Although neither of the instances analyzed were examples of autonomous decision devices, as relational model-base structures evolve, the capability of relational model-base structures to be invested with decision-making authority over certain operational tasks will increasingly be added by organizations who find value in deploying active decision models as decision support and implementation systems.

On Relational Model Bases and Organizational Design

The critical impetus for the introduction of additional decision technologies that aid in real-time, organizationally integrated decision making is modern business' movement from producing primarily goods to primarily services. This progression places decision-making processes at the forefront of modern corporations, in some cases more important than object-producing processes (Simon, 1973). What sets excellent organizational performers apart is the quality, speed and execution of their organizational decision-making, particularly when it comes to the critical operational and tactical decisions requiring consistency and speed (Rogers & Blenko, 2006). Rogers & Blenko (2006) found that when addressing how organizations got to their vaulted position in relation to decision-making, two factors emerge: 1) introducing decision technologies that match technology to the limits of the attentional resources of the organization; and 2) adopting an organizational form or structure that seeks optimization over stability or continuity (Simon, 1973; Zuboff & Maxmin, 2002). Additionally, both of these factors would be prerequisites for the introduction of effective relational model-base structures into an organization. While each of these factors would seem immediately evident, organizations do not always recognize or espouse these success factors when choosing the technology they adopt for enhanced decision making.

Throughout the information era, information systems have been introduced into organizations in an attempt to provide information and knowledge to the organization, meeting with a tremendous degree of success. With the rapid development of information technology, organizational decision-making processes are immensely more sophisticated and rational than they were in past eras. No longer is information the scarce resource when an organization faces a decision, it is the amount of attention that decision makers have to pay to the decision factors and how fast the decision must be made (Simon, 1973). An information system that will improve the system's performance, such as a relational model-base structure, is one where its output is small in comparison with its input (data sources as inputs to the model), so that the information system conserves attention, instead of making additional demands on a decision maker's attention. Indeed, to conserve attention, relational model-base structures incorporate analytic and synthetic models that are capable, not merely of processing information, but also of solving problems, evaluating solutions and making decisions when invested with that authority, thereby improving the overall system performance (comprised of man and machine) of the organization. The most important requirement for handling complex organizational decision-making is the creation of one or more models, to provide coherence to the decision-making process, wherever organizationally the models are located (Simon, 1973). The delay in creating these much needed models, and in the adoption of relational model-base structures within organizations, is partly due to the novelty of looking at an organization as a collection of decision systems, rather than a collection of departments, with the initial pause stemming from the lack of technological tools needed to create these models.

Current decision-making scholarship identifies cross functional (inter-departmental) collaboration as a weak point in organizational decision-making, as often there is a lack of clarity about who has decision-making input and execution authority within the organization (Rogers & Blenko, 2006). This lack of clarity is a direct result of decision responsibility not being clear when cast in the light of departmental compartments. Eliminating these cross-functional bottlenecks has less to do with shifting decision-making responsibilities between departments and more to do with ensuring that people with relevant information are allowed to share it, by identifying the individual's or group's decision role, versus functional role, in the organization, thereby making clear who has input to the decision and who gets to decide. In an organization that excels in its decision-making processes, decision roles would trump the functional organization chart, with the organization reinforcing decision roles. This could be extended to include inter-organizational decision processes as well.

This leads into the second factor for excellence in organizational decision making, which is adopting an organizational form or structure that seeks optimization over stability and continuity. Economists and management scholars tend to view organizations and managers as rational actors who seek to optimize the firm's performance. But another kind of theoretical perspective gaining ground in economics and organizational studies emphasizes the unique properties of organizations and their preference for behavior that promotes stability and continuity over optimization (Zucker, 1977, 1988). This means that institutional behavior conforms to the dictates of established authority, not to the laws of the marketplace. Therefore, while many will say that the mass production model of the organization and its primary focus on producing objects is dead, few will accede to the fact that the underlying organizational structure of mass production must change (Zuboff & Maxmin, 2002). While a shift in organizational focus should lead to a shift in organizational structure to address the new focus, the standard enterprise logic is organized to reproduce itself at all costs (undergo autopoiesis (Maturana & Varela, 1980) , similar to all living systems), even when it is commercially irrational to do so. A movement away from the organizational structures of transaction economics and managerial capitalism toward those of relationship economics and distributed capitalism will be essential to optimizing organizational decision making to address complex marketplace and policy scenarios. The relationship between transaction economics with managerial capitalism and relationship economics with distributed capitalism is one of hierarchical integration, where many of the elements of transaction economics – supply and demand, profit, return on investment, return on capital, operating cash flow, etc. – continue to exist within relationship economics, but they are now organized in a more complex system that is oriented toward the new purpose of relationship value realization. Distributed capitalism paves the way for more horizontal, less hierarchical forms of social organization, as well as methods of distributing authority and power that emphasize coordination and collaboration over administration and fragmentation (Zuboff & Maxmin, 2002), those that would benefit most from decision technologies such as relational model-base structures.

Future Research Possibilities

The directions for further investigation with their genesis in this dissertation are myriad in scope and nature. Depending on the focus of the particular investigation, many different areas of study could be involved. A most natural extension of this work would be a more formal proof of relational model-base theory. While a solid beginning of the conceptual basis has been laid out, a more rigorous mathematical treatment would be a significant contribution to the advancement of relational model bases as decision technology. The development of mathematical constructs to explicate Type 5 and Type 6 manifold network models would also be a contribution in formalizing the interconnections between decision models in a more general fashion.

Additional case studies, such as the ones presented for agricultural e-commerce and ecological economics, could be conducted to further investigate the economic benefit of the introduction of relational model-base structures into various industries and organizations. While the two cases chosen were designed to be representative of two situations of organizational decision-making constraints (hierarchical and non-hierarchical), it is quite possible that further case studies would provide additional information related to the application of relational model bases in organizations.

As a corollary to this line of study, detailed analyses of additional instantiations of relational model-base-type structures that appear within organizations already (in addition to the two that were provided in this study) would be a contribution by allowing further inquiry into the situations where relational model-base structures would add the most economic and practical value. While a few particular organizational situations appear ripe for the application of relational model bases, it is also perfectly plausible that other scenarios exist where these relational model-base-type systems have already been applied. Looking for more examples of these natively occurring instantiations could shed light on these additional situations for which relational model bases are well-suited.

Perhaps the most interesting future research direction would involve future investigation of the implications for organizational design that relational model-base structures being introduced into the organization would effect. There is no doubt that one intended effect of the introduction of relational model-base structures would be more tightly integrated organizational entities related to each other in their decision-making authority. However, this augurs many other changes to an organization and its processes that would be worthy of investigation, including effects on formal organization charts as the result of empowering decision entities within the organization outside of the traditional "department" structure and the rapid constitution and dissolution of virtual corporations based on tasks executed using relational model-base structures through alteration of supply chains and value delivery networks.

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