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Relational Model-Base Structures: a Hierarchical Application in Precision Agriculture

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ABSTRACT

The relational model base system represents a significant departure from the data-base dependent decision models that currently exist when discussing real-time data analysis and decision making. This research involves detailing cases of prototypical relational model-base-centered integrative systems and the incorporated relational model-base structures for each system as proposed by Sutherland and Baker (2007). The specific instance of dynamic resource allocation outlined here discusses a recursive agribusiness case, with the target application being precision agriculture, alternatively known as precision farming. In this research, 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 a 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.

Keywords

Decision support systems, Relational model-bases, Real-time decision-making, Precision agriculture

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.

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 and 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 and 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 specific planting decisions.

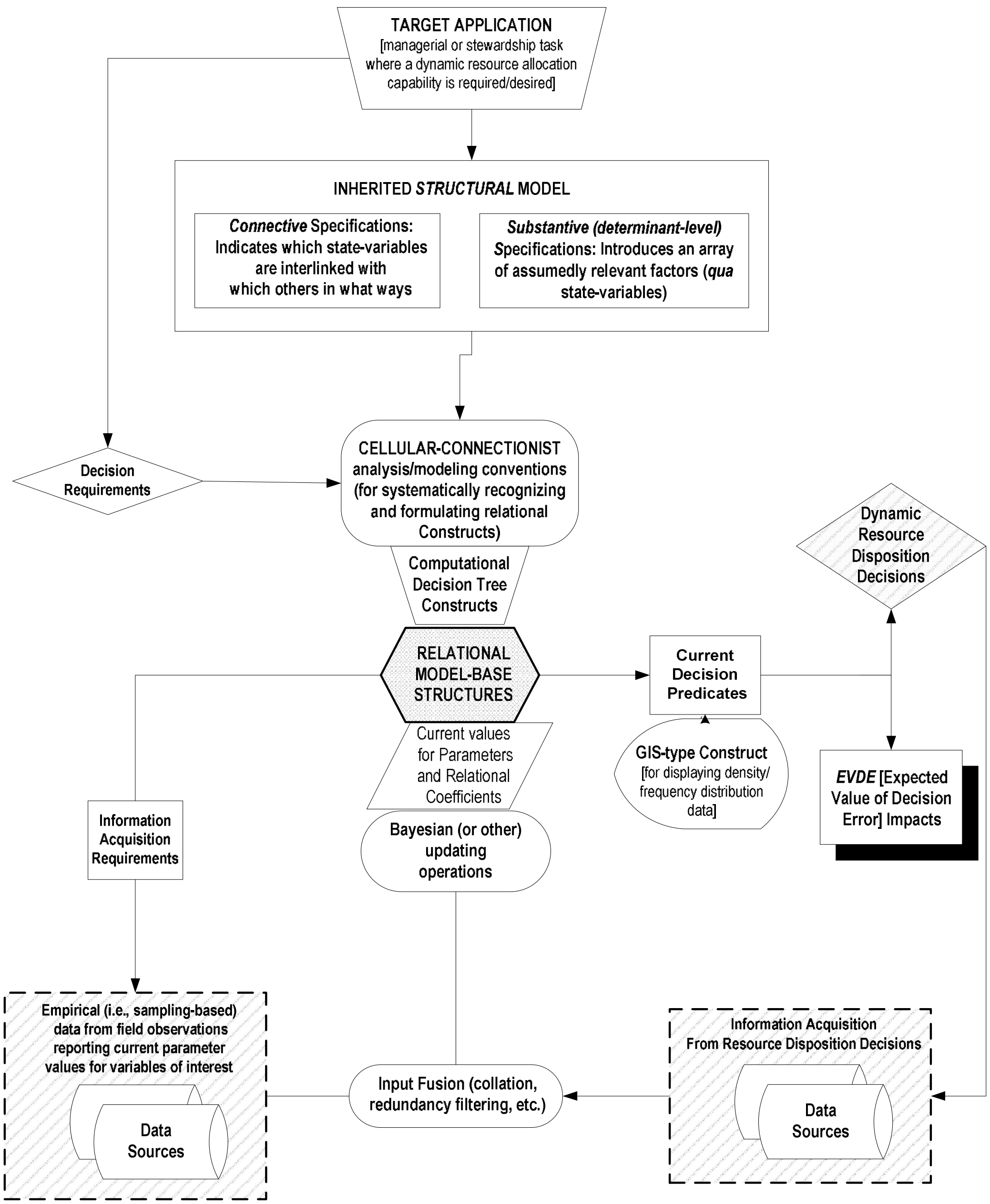

Figure 1. A prototypical relational model-base-centered integrative system

This research involves detailing cases of prototypical relational model-base-centered integrative systems and the incorporated relational model-base structures for each system as proposed by Sutherland and Baker (2007). A diagram of a generic prototypical relational model-base-centered integrative system appears in Figure 1. The specific instance of dynamic resource allocation outlined here discusses a recursive agribusiness case, with the target application being precision agriculture, alternatively known as precision farming. Precision agriculture is an agricultural concept relying on the existence of in-field variability. It requires the use of new technologies, such as global positioning (GPS), sensors, satellites or aerial images, and information management tools (GIS) to assess and understand variations. Precision farming may be used to improve a field or a farm management from several perspectives: better fertilization management; better time management at the farm level; better estimation of crop nitrogen needs implying limitation of nitrogen run-off; increase of the output and/or reduction of the input, with lower cost of nitrogen fertilization practice. 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 Luvall Shaw Mask Kissel and Sullivan 2003).

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 research is as follows: after the relational model-base-centered integrative system for the grain producer is detailed, based on Figure 1, 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 optimize 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. 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 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 chose 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 1. This example will be further explicated in the next section with initial parameters set for the m_x and b_x variables, with m_x and b_x being relational constants that are dependent on the specific farm/planting environment.

	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	
Connective Specifications (Elementary Relational Operators)	v_2 is ↑ (positively and proportionally) related to v_1 v_3 is ↑ (positively and proportionally) related to v_1 v_4 is ↑ (positively and proportionally) related to v_1 v_2 is ⇒ (dependent on (dominated by)) level of current soil moisture, s_o	$\boldsymbol{r_x}$**(1 ∩ 2):** v_2 is ↑ (positively and proportionally) related to v_1 $\boldsymbol{r_x}$**(1 ∩ 3):** v_3 is ↑ (positively and proportionally) related to v_1 $\boldsymbol{r_x}$**(1 ∩ 4):** v_4 is ↑ (positively and proportionally) related to v_1 $\boldsymbol{r_x}$**(2 ∩ 3):** v_2 is ↑ (positively and proportionally) related to v_3 $\boldsymbol{r_x}$**(2 ∩ 4):** v_2 is ↑ (positively and proportionally) related to v_4 $\boldsymbol{r_x}$**(3 ∩ 4):** v_3 is ↑ (positively and proportionally) related to v_4
Substantive Specifications (Computational Functional Relationships	$v_2 = m_2v_1 + s_o + b_2$ $v_3 = m_3v_1 + b_3$ $v_4 = m_4v_1 + b_4$	

Table 1: Variables, connective and substantive specifications (the inherited structural model) and relational model-base substructure for an illustrative example in precision agriculture

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 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. In the move toward more real-time decision making, it is in this area 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 any 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 2. 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.

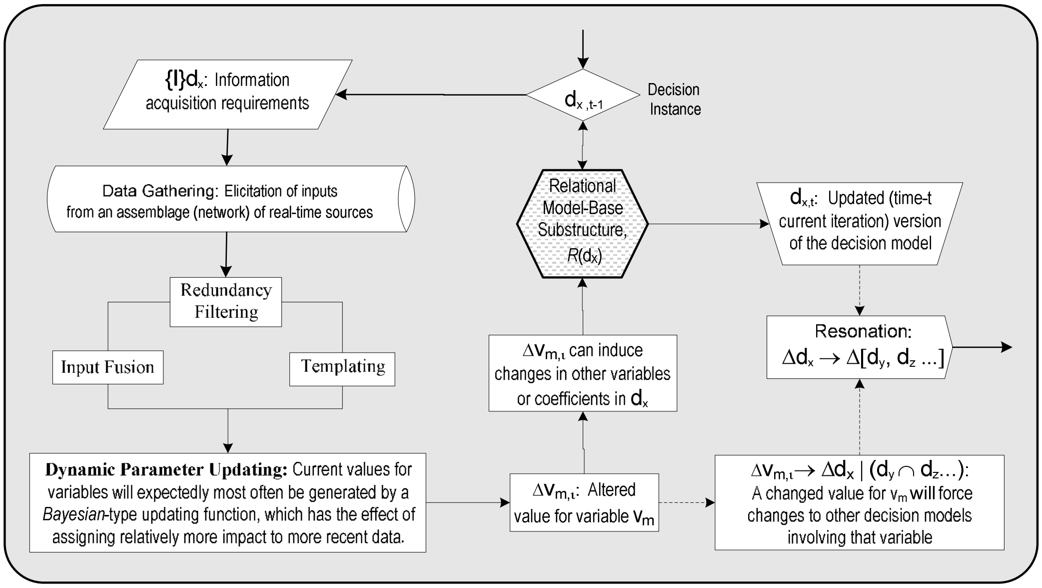

Figure 2: Dynamic Parameter and Model Updating using Bayesian Updating Functions in a Relational Model Base

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 1 depicts, the relational model-base system consists of five interrelated parts: the relational model-base structure; 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 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 1 earlier in this chapter 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 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 1, at the elementary relational operator level, $r_x(v_m \cap v_n)$ □ 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 $d_x = R(v_1 \cap v_2 \cap v_3 \cap v_4)$, which is detailed in Table 1 as the substantive specifications, and R 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 (Blue Andoh-Baidoo and Sutherland 2006). The scenario of the grain producer and miller presents no exception to a dependent or co-dependent decision-making model.

	Relational Substructure $R(d_x)$			
	$\upsilon_1 = v_{1,\,t\text{-}1}$	$\upsilon_2 = v_{2,\,t\text{-}1}$	$\upsilon_3 = v_{3,\,t\text{-}1}$	$\upsilon_4 = v_{4,\,t\text{-}1}$
$v_1 = v_{1,\,t}$	ϕv_1	$f(1,2) = f(2,1)$	$f(1,3) = f(3,1)$	$f(1,4) = f(4,1)$
$v_2 = v_{2,\,t}$	$f(2,1)$: $v_2 = m_2 v_1 + s_o + b_2$	ϕv_2	$f(2,3) = f(3,2)$	$f(2,4) = f(4,2)$
$v_3 = v_{3,\,t}$	$f(3,1)$: $v_3 = m_3 v_1 + b_3$	$f(3,2)$: $v_3 = m_3((v_2-b_2)/m_2) + b_3$	ϕv_3	$f(3,4) = f(4,3)$
$v_4 = v_{4,\,t}$	$f(4,1)$: $v_4 = m_4 v_1 + b_4$	$f(4,2)$: $v_4 = m_4((v_2-b_2)/m_2) + b_4$	$f(4,3)$: $v_4 = m_4((v_2-b_2)/m_2) + b_4$	ϕv_4

Table 3: Configuration Features of Relational Model-Base Substructures for Planting Decision Model (d_x) in Agricultural Case

In the scenario of the grain producer, the relational model base structure itself would be constructed based on the cellular-connectionist analysis. Table 3 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 3.

In a time series example, ϕv_1 describes the relationship between v_1 and υ_1 at time t. It is used to compute the value of v_1 at time t based on the value of v_1 at time (t-1), which is υ_1. ϕv_1 is not defined algorithmically in this current example, as the value of v_1 and υ_1 are not related computationally. The value for v_1 at any given time is based on GPS input function data describing the planting terrain. 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 functions ϕv_2, ϕv_3, and ϕv_4 are also not defined algorithmically in this particular example. 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.

	υ_1	υ_2	υ_3	υ_4
t = 0	10	20	1	3
t = 1	20	40	2	6
t = 2	5	10	0.5	1.5
t = 3	10	20	1	3

Table 4: 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 $b_4 = 0$)

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 grain producer. Table 4 shows the actual values for running the relational model base for a typical , 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. At each time t, 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-word 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. Prototypes of relational model-bases in precision agriculture have already been developed. 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. 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.

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 4. 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.

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. 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, D is the set of decision requirements for the task involved of the grain producer providing the miller with the grains he 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. Table 5 presents the decision-tasking table for this illustrative 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)

Table 5: Decision Tasking Table for Illustrative Agricultural Example

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 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. 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.

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.

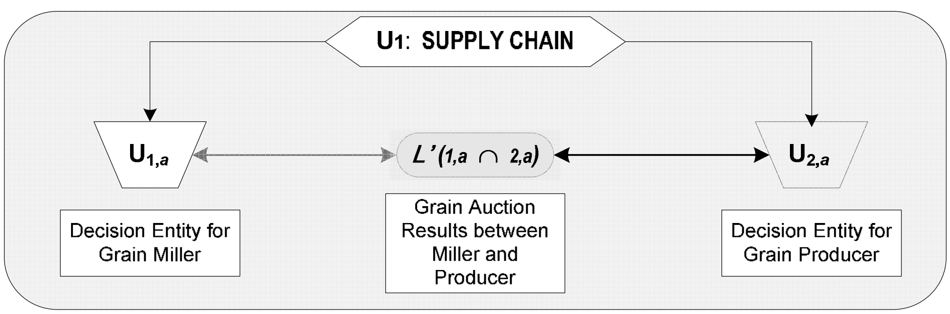

Figure 3: Conventional Organizational Construct for Illustrative Agricultural Example

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 3 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 miller 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 producer 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 and so all of equivalent authority in this decision-making scenario. 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 3 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, forming the lateral integrative linkage between the entities. Time is not a factor in Figure 3; the grain auction results acting as the lateral linkage between the two entities does not change over time. It is probable that the terms of the auction will change over time, 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.

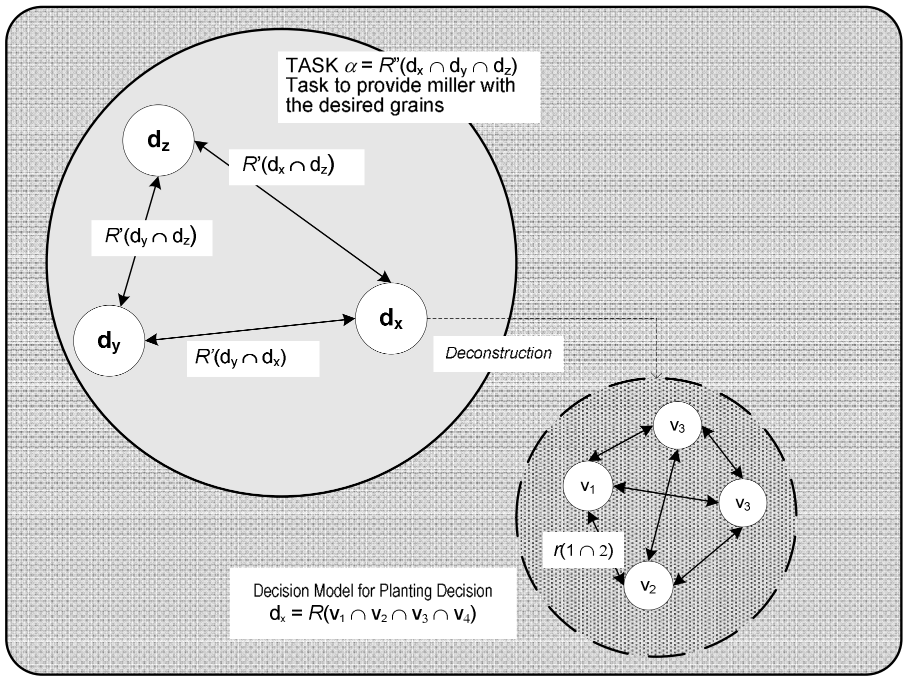

Figure 4: Cellular-Connectionist Relational Model-Base Construct for Illustrative Agricultural Example

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.

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