Communications of the Association for Information Systems

Volume 33 Article 23

12-2013

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Communications of the Association for Information Systems

CAIS

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Abstract:

This article presents a technical approach to acquiring quality, real-time decision-making information within organizations and illustrates this approach with an extended case study. Using relational model bases for real-time, operational decision making in organizations facilitates a transition to dynamic (vs. forecast-driven) resource allocation decisions. These and related systems offer development of a new generation of DSS applications which can be applied to extend preemptive decision making across many industries. This approach is illustrated through a description of a detailed conceptual case (scenario) pertaining to its application in agribusiness. This approach to decision making can be viewed as an extension of well-known techniques pertaining to DSS but also represents the opportunity to address problems not amenable to traditional post hoc analysis. Researchers can learn from the accumulated knowledge pertaining to DSS but can also examine innovations that push forward into new territories. The article presents and discusses a variety of emergent research questions prompted by the application of these technologies in the business environment.

Keywords: organization, decision support systems, real time, business intelligence, relational model base

Editor's Note: The article was handled by the Department Editor for Special Section on Emerging Ideas and Topics in IS

Volume 33, Article 23, pp. 393-406, December 2013

The manuscript was received 05/15/2012 and was with the authors 6 months for 2 revisions.

I. INTRODUCTION

The development and deployment of RFID sensors, massive Web-based data (e.g., network traffic, user clicks, etc.) and many other new sources of streaming data offer many operational opportunities for industries as diverse as supply chain management and health care. The prevalent model of DSS would integrate incoming data with other organizational information largely for the detection of patterns and to aid in long-range decision making. This will continue to be an important and profitable function of DSS.

However, achieving full value from these streams of data requires new organizational approaches to fully utilize them in predictable and innovative ways [Niederman, Mathieu, Morley and Kwon, 2007]. Although one approach to using this data involves traditional storage and analysis, it has been argued that additional uses are conceivable that will take better advantage of the real-time processing of the enormous volume, velocity, and variety of data that these sources make available [McAfee and Brynjolfsson, 2012]. This approach focuses on automated analysis of data as it arrives rather than post hoc analysis after operational activities have been completed. Such a priori processing offers an approach to address competitive situations that require actionable information much more rapidly than ever before, minimizing lengthy (or impossibly complex) processing. From a strategic perspective, firms are challenged to ensure the real-time availability, agility, and adaptability of information, both internally and externally, required for handling dynamically changing business and competitive environments [Prahalad, 2009; Kohli and Grover, 2008; Sambamurthy, Anandhi and Grover, 2003; Mithas, Ramasubbu and Sambamurthy, 2011]. The ability to develop more flexible operational responses during the processing of transactions can represent a strategic approach or advantage relative to firms without that level of flexibility. Tesco, a bricks-and-mortar UK grocer, gathers transaction data on its 10 million customers and uses the information to analyze new business opportunities—for example, how to create the most effective promotions for specific customer segments. They further apply data to inform their strategic direction using data to inform decisions on pricing promotions and shelf allocation. Fresh Direct, a U.S. online grocer, shrinks reaction times even further to adjust prices and promotions daily or even more frequently, based on data feeds from online transactions, visits by customers to its website, and customer service interactions. In healthcare the University of Ontario Institute of Technology and Toronto's Hospital for Sick Children use real-time data collected from premature infants in its nursery to detect earlier hospital-acquired infections in these infants, enabling the children to be treated before the situation becomes life-threatening [Baluja, 2012].

One approach to such automated decision processing is real-time processing which can be expected to make available the most current data upon which to base business intelligence [Duan and Xu, 2012; Watson and Wixom, 2007]. The current approach to enacting real-time processing uses active data warehouses and push-based BI (made possible with the arrival of large quantities of addressable RAM). Using underlying technologies such as complex event processing and event correlation, operational intelligence analytics are a step in the direction of finding and extracting information before it heads into the data warehouse, where the time to retrieve the information again increases significantly. Operational intelligence allows for operational data that does not need to be loaded into the warehouse before analysis, as the arrival of events in the data input stream triggers processing of the query.

However, even with the application of these techniques, organizations are still reliant on fixed models. To achieve true real-time BI systems need to "learn" or adapt from the data being streamed in during the data acquisition stage to update and/or replace decision models [Blei, 2012; Chandy and Schulte, 2010; Marjanovic, 2007]. Once instantiated, these complex, adaptive systems would take streaming data and allow for algorithmic data decision-making interaction.

One promising approach to moving toward such "true" real-time processing may be based on the use of model bases to process the data [Davenport and Harris, 2005]. As an active, model-driven DSS class [Power, 2008], relational model bases address transaction and process automation with internal, integrated processes when deployed as an organizational decision support system (ODSS) [Carter, 1992; Eom, 2007; George, 1992] and has the potential to be deployed to support transaction and process automation with inter-organizational (peer) processes when deployed as an inter-organizational system (IOS) [George, Nunamaker and Valacich, 1992; Sen, Moore and Hess, 2000].[1] Cohen, Kelly and Medaglia [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.

Relational model bases exist today in very basic instantiations where models can be changed only manually. Conceptually, relational model bases are an emerging technology that would allow input data to add, update, or delete aspects of the *models* upon which input data is processed autonomously, in addition to being able to alter the parameters of the model. A relational model-base structure as a class of active, adaptive DSS [Holsapple, Pakath, Jacob and Zaveri, 1993; Jacob and Pirkul, 1990; Manheim, 1989; Mirchandani and Pakath, 1999] acts as an integrative device by relating an organization's elementary relational functions to each other in models prior to data acquisition with a model management system at its core to build, analyze, and maintain models *dynamically as the system inputs and elementary relational functions evolve* [Liu and Tuzhilin, 2008; Muhanna and Pick, 1994]. Sutherland and Baker [2007] show that relational model bases 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.

It is important to keep in mind that while relational model bases provide an opportunity to provide value by capturing and exploiting real-time data for decision making and action taking, they are not likely to be as successful if applied to inappropriate tasks. Appropriate tasks must involve situations with regular decision instances, when the decisions are recurrent and routine. The decision task must also admit to a conventional, technical, algorithm-driven solution for which decision choices are deterministic or probabilistic in nature. In organizations where a premium is placed on real-time propositional decision functions and near-instantaneous decision execution, instantiations of relational model-base structures would serve to provide these organizations with a mechanism to analyze the propositional decision functions in *real time*. Proctor and Gamble uses real-time data to monitor conditions so that if supplies are delayed due to weather, traffic, or other causes, the systems will use the data to create alternative delivery scheduled to ensure that production facilities get the appropriate supplies in sufficient quantities [O'Leary, 2008]. Real-time data in healthcare can help clinical decision making at the individual level and the population level by interpreting and monitoring patient data for diagnosis, establishing benchmarks and alerts to help with chronic disease management, and detecting pandemic diseases or tracking chronic diseases, aiding overall public health surveillance [Basu, Archer and Mukherjee, 2012].

This work addresses an open research question in the domain of real-time business intelligence [Ranjan, 2008]. A gap exists in this research regarding tools that would allow for the real-time synthesis of data *prior* to processing into a warehouse for decision makers, either solitary decision makers or groups charged with making a decision. This research path is taken in response to a plea made by several IS researchers concerned that this area might be overlooked by the IS field at a critical moment during this intense focus on "Big Data" and its potential impacts [Chen, 2011; Chen, Chiang and Storey, 2012]. This research also addresses the industry need to shorten the time lag between data acquisition and decision making [Chaudhuri, Dayal and Narasayya, 2011]. The research question addressed is: What are the technical requirements when an information system must process information prior to its being stored in the data warehouse, delivering output that is algorithmic to make automated decisions, or easily interpretable by a human decision maker for real-time decision making?

Relational model-base structures are presented in the following section, followed by a discussion of the potential impacts of IS research that could be done in this area throughout several knowledge domains. One approach to responding to this challenge of implementing such a system will be presented based on a case within the field of precision agriculture. Precision agriculture is the field of whole-farm management with the goal of optimizing returns on inputs (economics) while preserving resources (environmental conservation) by matching farming practices more closely to crop needs (crop science). The exemplar relational model base is applied to precision farming, a farming management concept based on observing and responding to intra-field variations. The article concludes with a discussion of additional areas to which this technical solution could be applied and the potential impact of the widespread adoption of these systems in organizations.

[1] Relational model bases are not to be confused with relational database management systems (RDBMS). In RDBMS, decision models can be built, but their processing does not vary dynamically based on the input data as it is processed. Of course, a technologist can reprogram the decision models within the RDBMS; however, such reprogramming will be inefficient (e.g., requiring scheduled human labor) and will invoke a delay (e.g., finding the need to reprogram, taking the time to change the model, testing the new design, and running the new model).

II. RELATIONAL MODEL-BASE STRUCTURES: A RECURSIVE APPLICATION IN PRECISION AGRICULTURE

Agriculture is one commercial endeavor where there is a clearly identified need to improve operational efficiencies by integrating processes between participants at various levels [Henderson, Akridge and Dooley, 2006; Ernst and Tucker, 2002]. Additionally, the need for real-time information processing to facilitate more efficient agricultural decision making, including the introduction of more sophisticated decision technologies, also has been identified [Diekmann and Batte, 2010; Hirafuji, 2000; Massey, Myers, Kitchen and Sudduth, 2008; Schiefer, 2003]. As an industry in the U.S. alone, agribusiness is a 2.4 trillion USD industry with an annual growth rate of 1.5 percent [Kruchkin, 2012]. Precision agriculture systems and services, a subset of the agribusiness industry, has U.S. revenue of 1.3 billion USD with annual growth projected at 6.1 percent [McBee, 2012]. The robust growth rate reflects that technological innovations within precision agriculture systems will make the technology more compelling to implement, in spite of farmers' general lack of technological sophistication as a group [Kitchen, Snyder, Franzen and Wiebold, 2002; Omidi-Najafabadi and Bahramnejad, 2010]. The adoption and diffusion of precision agriculture will increase as penetration of broadband and mobile technologies in rural areas grows and educational efforts achieve further success [Kitchen, 2008; Lamb, Frazier and Adams, 2008]. Worldwide, the growing demand for agriculture products and services from newly industrialized countries will make the use of precision agriculture more attractive [Omidi-Najafabadi, Hosseini and Bahramnejad, 2011].

More importantly than market size, precision agriculture is a clear example of how relational model bases can be used to improve sustainability in the global food supply [Walsh et al., 2006] and improve farmers' profitability [Rickman et al., 2003], encouraging a more rapid adoption of the technologies. Having these precision agriculture technologies contribute to the sustainability of agricultural systems stressed by increasing food and biofuel demands is a critical humanitarian issue. Population growth is expected to increase, and world population is projected to reach 10 billion by 2050. This population growth decreases per capita arable land. More intensive agricultural production will have to meet the increasing food demands for this increasing population, especially because of an increasing demand for land area to be used for biofuels [Delgado and Berry, 2008; McConnell and Burger, 2011].

This case is developed in the context of agribusiness, 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 (many kilometers square 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. 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 farmland 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 subfield 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.

The introduction of relational model bases to this scenario is 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 benefits of applying real-time BI to precision farming also include the integration in real time of decision models by the relational model base, allowing the farmer to invest decision authority in the model-base system, 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. A diagram of a generic prototypical relational model-base-centered integrative system appears in Figure 1.

In this generalized conceptual case, the 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. The outline of this article is as follows: after the relational model-base-centered integrative system for the grain producer is detailed, based on Figure 1, the relational model-based structures will be outlined, followed by a discussion of how large quantities of inputs to create and modify models would be handled by this system. This

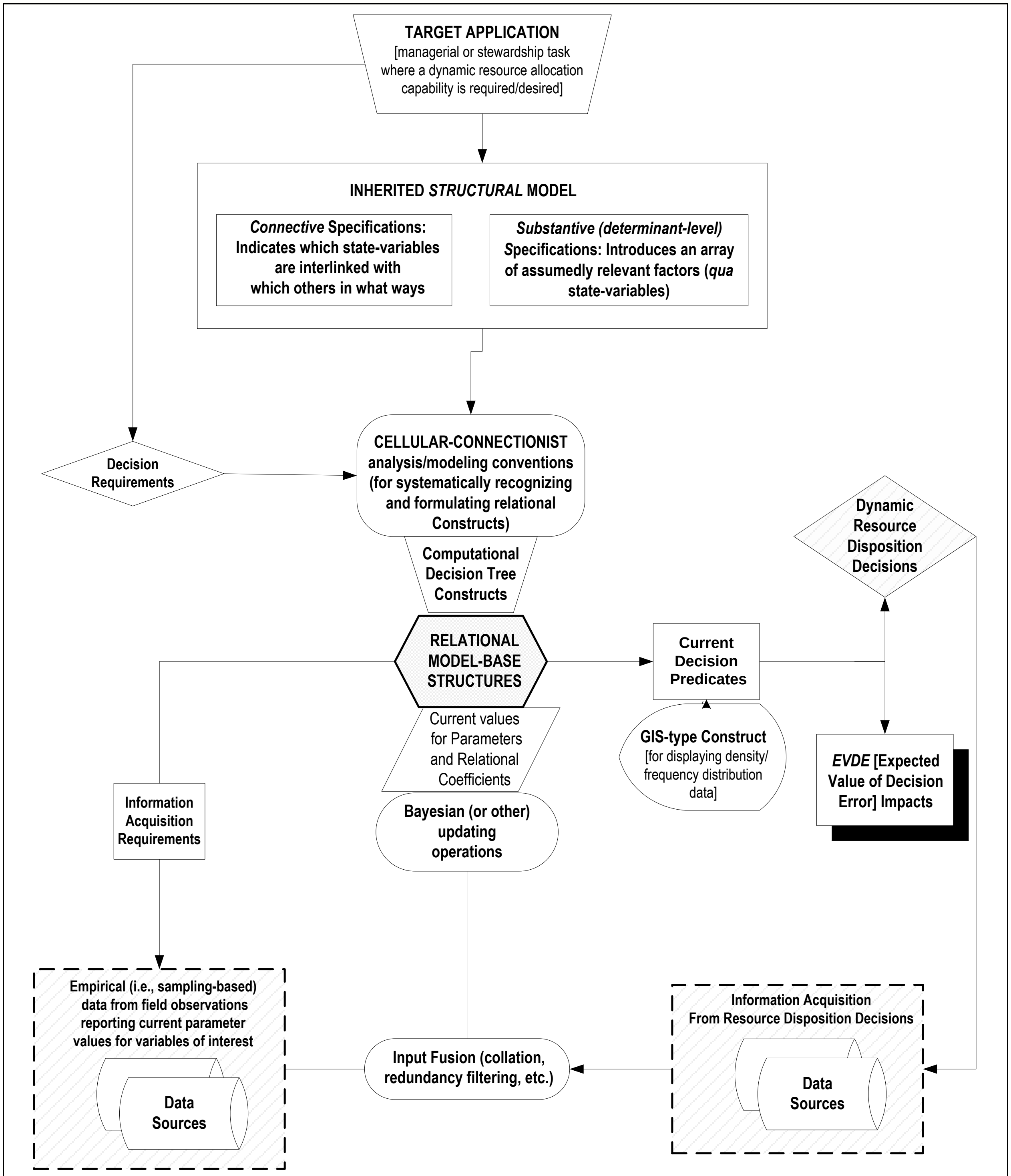

Figure 1. A Prototypical Relational Model-base-centered Integrative System

article concludes with a discussion of possibilities and implications of relational model base implementation in the enterprise.

III. A GRAIN PRODUCER'S RELATIONAL MODEL BASE AND ITS CHARACTERISTICS

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. Figure 2 shows what a relational model-base structure would look like in a real-time, decision-making system applied to precision farming.

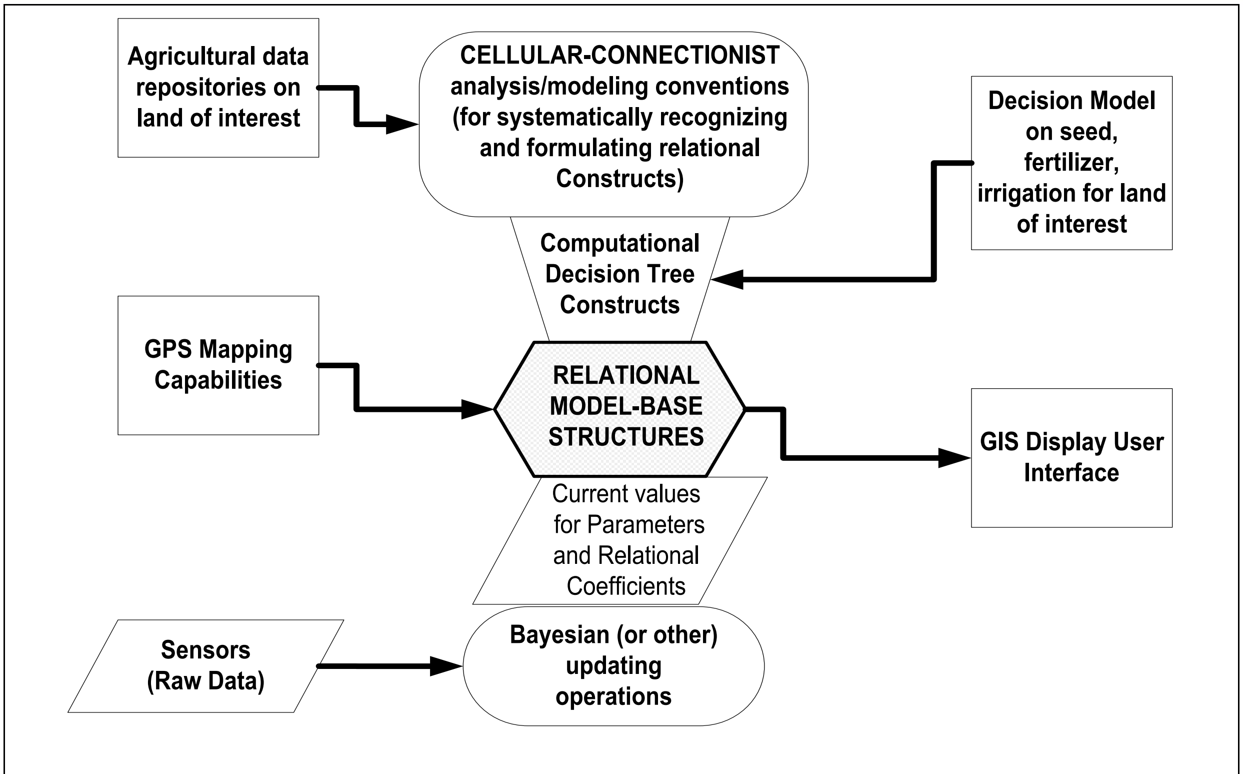

Figure 2. A Relational Model Base Model with an Example from Agribusiness

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. An example of the complexity of one model involved is presented in Kim, Sudduth and Hummel [2009], who model soil macronutrient sensing for precision agriculture.

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 (b_x) and relational coefficients (m_x) that would inform the grain producer's relational model-base structure in a real-world example. For the purposes of a vastly simplified illustrative example, in Table 1, we 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.

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 (among others) temperature and composition of the soil, weather conditions on the site, fertilizer residue present in the soil, and moisture conditions of the soil. 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

Table 1: Inherited Structural Model and Substructure for Agribusiness Example		
	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	$\boldsymbol{r_x(1 \cap 2)}$: v_2 is ↑ (positively and proportionally) related to v_1 $\boldsymbol{r_x(1 \cap 3)}$: v_3 is ↑ (positively and proportionally) related to v_1 $\boldsymbol{r_x(1 \cap 4)}$: v_4 is ↑ (positively and proportionally) related to v_1 $\boldsymbol{r_x(2 \cap 3)}$: v_2 is ↑ (positively and proportionally) related to v_3 $\boldsymbol{r_x(2 \cap 4)}$: v_2 is ↑ (positively and proportionally) related to v_4 $\boldsymbol{r_x(3 \cap 4)}$: v_3 is ↑ (positively and proportionally) related to v_4
Substantive specifications (computational functional relationships)	$v_2 = m_2v_1 + s_o + b_2$ $v_3 = m_3v_1 + b_3$ $v_4 = m_4v_1 + b_4$	

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 [Kitchen, 2008]. 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, aggregation, redundancy filtering, and templating. 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 2 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; computational decision tree constructs; 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 article 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. 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, $r_x(v_m \cap v_n) \in d_x$, 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 $d_x = R(v_1 \cup v_2 \cup v_3 \cup v_4)$, 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 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.

Table 2: Relational Model-Base Substructures' Configuration Features for Planting Decision Model (d_x)

	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	$f(1,2) = f(2,1)$	$f(1,3) = f(3,1)$	$f(1,4) = f(4,1)$
$v_2 = v_{2,\,t}$	$f(2,1)$: $v_2 = m_2v_1 + s_o + b_2$	ϕv_2	$f(2,3) = f(3,2)$	$f(2,4) = f(4,2)$
$v_3 = v_{3,\,t}$	$f(3,1)$: $v_3 = m_3v_1 + b_3$	$f(3,2)$: $v_3=m_3((v_2-b_2)/m_2)+b_3$	ϕv_3	$f(3,4) = f(4,3)$
$v_4 = v_{4,\,t}$	$f(4,1)$: $v_4 = m_4v_1 + b_4$	$f(4,2)$: $v_4=m_4((v_2-b_2)/m_2)+b_4$	$f(4,3)$: $v_4 = m_4((v_2-b_2)/m_2)+b_4$	ϕv_4

Table 2 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 2.

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 or her 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 or her location in the field. The functions ϕv_2, ϕv_3, and ϕv_4 also are 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.

Table 3: Relational Model-base Output for Planting Decision Model (d_x)

	(m2 = 2; m3 = 0.1; m4 = 0.3; b2, b3 and b4 = 0)			
	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

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 3 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. At each time t, the amount of seed to be planted is fed into 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 real-world precision farming, every acre of land would have readings of the input variables taken in real-time from remote wireless sensors and satellite data streams as the turbine/tractor covers the ground distributing the seed and tailored mixture of P, N, and K. With the large size of such farms (tens of thousands of meters) and the pace with which this farm equipment must cover such plots for the optimal farming output, real-time processing is needed to determine the outputs from the large volume of inputs and the decision models that are employed.

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. 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 [Jones and Taylor, 2004].

The key aspect of relational model bases that make them a new type of DSS is that this quality assessment could subsequently be used to generate better decision models *in real time*, in collusion with the incoming data acquisition requirements, acquired from RFID sensor arrays, for example. 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 3. 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 in the likely event that 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." How parameters and models are updated in a relational model-base structure is shown in Figure 3.

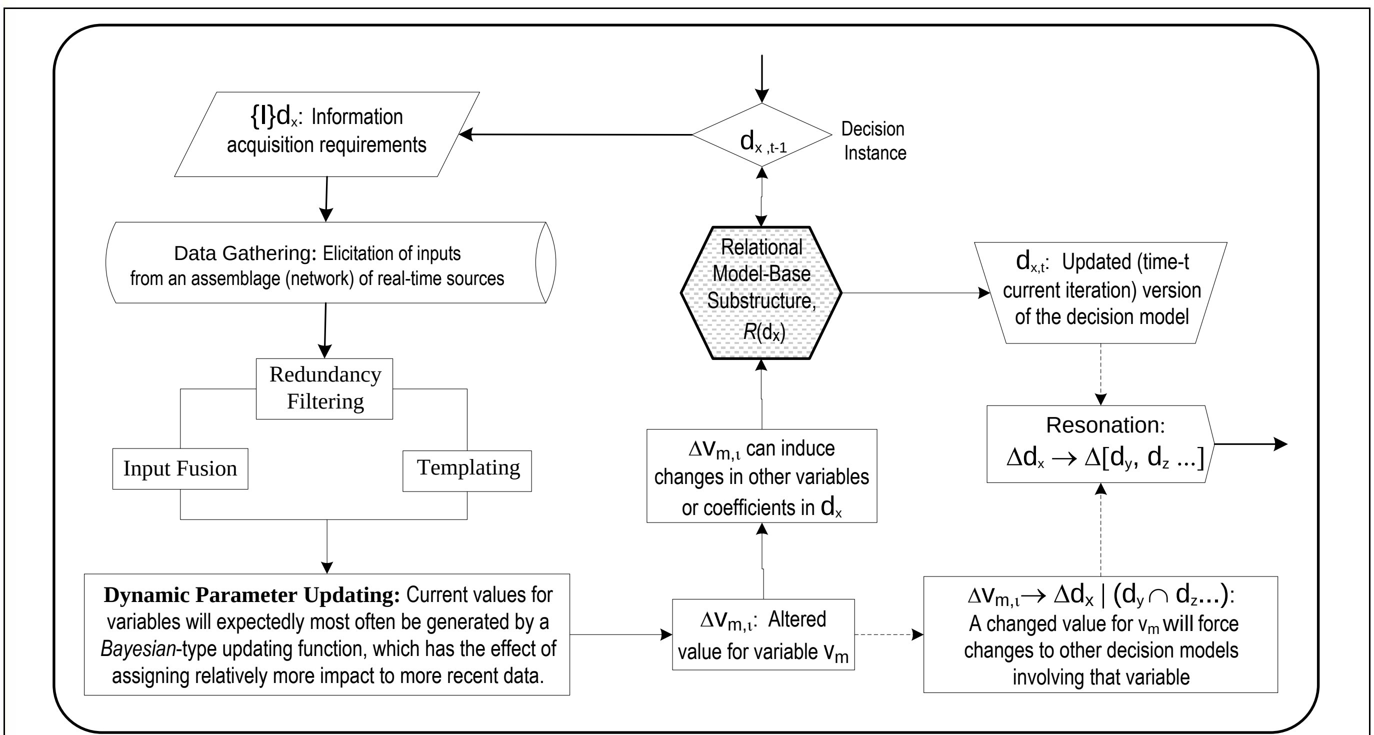

Figure 3. Dynamic Parameter and Model Updating Functions in a Relational Model Base

IV. ECONOMIC IMPLICATIONS

The goal of the enterprise is to establish optimal profit margins for the organization. For probabilistic decisions where the decision maker is risk averse, such as those present in precision agriculture, 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 4.

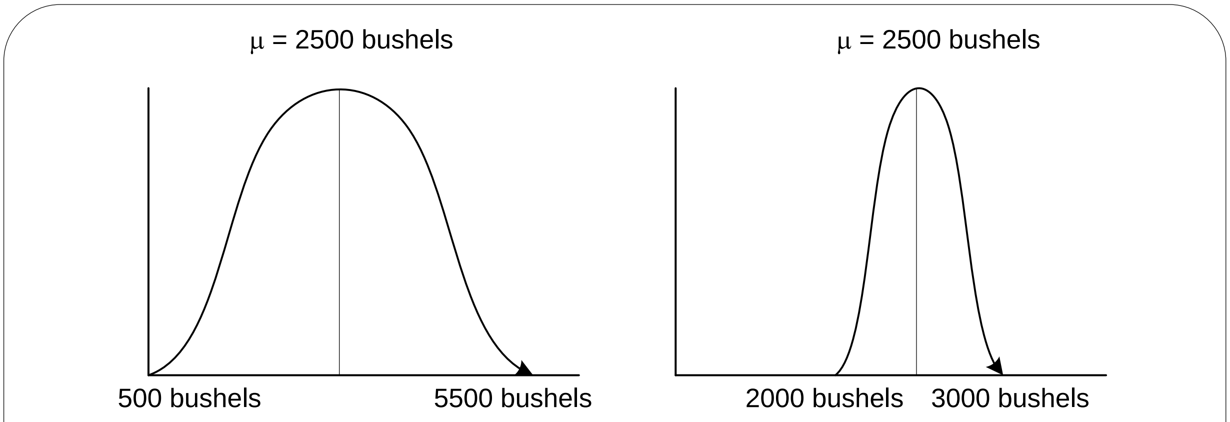

Figure 4a: EVDE of Decision without a Relational Model Base structure

Figure 4b: EVDE of Decision with a Relational Model Base structure

Figure 4. The Expected Value of Decision Error Using a Relational Model-base Structure

The distribution in Figure 4a, 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 than the distribution in Figure 4a, which is based on a less complete information base. In both distributions, μ 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 4b'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 4b. This results in a reduction in the expected value of decision error (EVDE), defined as the probability multiplied by loss for all $| \mu\text{-}\alpha |$, where α is any value included in the range of the probability function.

The distribution in Figure 4b has a lower EVDE than that in Figure 4a 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 4a–area in Figure 4b). 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. Over time, the investment in the system will generate positive returns stemming from this improved decision making.

V. DISCUSSION

Relational model-base structures are most well-suited to scenarios in which the decision outcomes are reasonably well-bounded. 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 inter-organizational, real-time, multi-criteria, multi-decision-making tools that can provide this capability. Therefore, the potential for these relational model base systems includes any decision-making scenario where real-time business intelligence is needed and where there is value in automating the decision making to provide this real-time data, providing a tool with the capability to solve many complex problems in several knowledge domains. These areas include public health and emergency services (i.e., pandemic response plans), bioinformatics, customer segmentation, and inventory management, in addition to the more widely recognized areas of fraud detection, risk management, financial modeling, and trade execution [Kloeckl, Senn and Ratti, 2012; Lederman and Wynter, 2011; Livengood, Maciejewski, Wei and Ebert, 2012; Maciejewski et al., 2011].

The case for the introduction of relational model bases is further strengthened by the fact that there already exist cases where propositional decision-function data goes into models and is processed in real time when response requirements in the situation are high. A representative example in finance is ActivePivot (quartetfs.com), a real time risk assessment tool for credit, market, counterparty, or liquidity risk, and an example in pandemic preparedness and public health is BioDiaspora (www.biodiaspora.com), a research project focused on the health implications of global population mobility. Although any of these scenarios could be chosen for investigation, this work looks in depth at a case in precision agriculture, detailing the appropriate conceptual model of the relational model base applied to this situation and discussing how this relational model base is reflected in the industry solution for real-time BI. Industry has developed relational model-base systems for use in precision agriculture and ecological reclamation projects, without those systems being termed as such. By looking at the work of those in industry who have deployed such solutions (e.g., IDLAMS (Integrated Dynamic Landscape Analysis and Modeling System) [Shoemaker, Dai and Koenig, 2005]), we can reevaluate and reposition the prior IS literature on real-time BI DSS to approach the problems we are encountering now that can be addressed by relational model bases.

VI. CONCLUSION

This work addresses an open research question regarding tools that enable the real-time synthesis of data *prior* to processing into a warehouse for decision makers, either solitary decision makers or groups charged with making a decision. This research path is taken in response to a plea made by several IS researchers concerned that this area might be overlooked by the IS field at a critical moment during this intense focus on "Big Data" and its potential impacts [Chen, 2011; Chen, Chiang and Storey, 2012]. The conceptual case presented is designed to illustrate how a relational model-base approach can address the opportunity presented by the explosion of data inputs and the need for dynamic models for real-time decision-making data. This work focuses on the technical requirements for implementing such a decision tool in an organizational setting. As the case is hypothetical, we would expect to learn more in the dialogue between technology constraints and organizational facts. Naturally much work remains in order to translate such a conceptualization into institutionalized everyday processes for placing these technologies regularly into business contexts.

In our view there are a number of directions for the extension of knowledge regarding this sort of technology. First, from a more technical perspective, the principles and examples described herein can (and likely will) be replaced over time with more specific and detailed sets of specifications. An accumulation of knowledge that distinguish more from less helpful approaches will ultimately save time from repeated trials and false starts. Second, from an organizational perspective, the range of tasks and the variations of technology required for successful implementation are not clear. Optimally tasks that are important, repetitive, and describable in models will be the "low hanging fruit," but how far can such tasks be pushed into the less repetitive, more complex, and even more quickly changing models? Third, from an historic perspective, contrasting both content and methods of development useful in DSS applications with those in the emerging relational model-base world can provide some basis for more quickly reacting to the next steps forward in decision-making technologies.

In the view of many, there is a Big Data revolution occurring where the growth of technology is leading to a deluge of decision-making data, while rapidly changing competitive environments demand business intelligence derived from this data to be available and applied in real time. Using relational model bases as a 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 can and are leading to a new generation of DSS applications in fields ranging from bioinformatics and agriculture to supply chain management and personalized marketing. This is the beginning of a new set of technical and behavioral research questions where IS researchers can seize the moment and make a significant impact on many knowledge domains, including the grand challenges of IS and engineering [Chen, 2011; National Academy of Engineering, 2008].

ACKNOWLEDGMENTS

The author would like to gratefully acknowledge the helpful comments of the reviewers and associate editor of this article.

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Communications of the Association for Information Systems

ISSN: 1529-3181