Context-aware Intelligent Model Selection System

Full Paper

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Abstract

After more than 40 years of research in computational decision support, model selection and management is still one of the most crucial problems. With organizations facing turbulences in an environment that include constant changes in social, political, technical and economic challenges, the selection of appropriate models for decision support has become even more difficult. Most research efforts do not consider model selection itself as a major aspect of research nor do they reflect on context awareness. The paper explores the early use of Artificial Intelligence (AI) techniques to improve model selection and reviews modern Intelligent Decision Support Systems (IDSS). Since model selection is a central problem for decision makers we specifically analyze research on model selection and identify important characteristics. Based on this analysis we suggest a framework and architecture for a Context-aware Intelligent Model Selection System (CIMSS). The paper concludes with further suggestions for future research.
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Keywords

Model selection, artificial intelligence, rule-based, model selection system, context-aware, decision support systems, MS/OR

Introduction

Model selection is a crucial issue for decision makers that has become even more difficult with organizations facing constant change in social, political, technical and economic challenges. As a result, no or not the most appropriate models are being selected, thus problem solving and decision making is often suboptimal.

The importance of model management has already been stressed more than 30 years ago (Konsynski and Sprague, 1986). Subsequent research has recommended improving MS/OR models for decision makers with AI techniques, especially Expert Systems (ES). It has been recognized that much can be gained from integrating the ES and DSS approaches since they can complement each other resulting in a powerful integrated, computer- based system that can vastly improve managerial decision making (Doukidis, 1988). In the following some prominent examples of this research are described.

Jarke et al. (1988) note that, at one extreme, there exists a large number of DSS and ES packages that have sophisticated user interface and model building technology but shallow model representation and, at the other extreme, operations researchers and others have developed sophisticated models and environments for creating and maintaining such models but these can be used only by specialists. This gap could be bridged by using AI methodologies leading to a faster transference of theoretical advances to practical applications.

Beulens and Nunen (1988) suggest a Process Control Management System (PCMS) that lies between the user interface and Data Base Management System (DBMS) and the Model Base Management System (MBMS) of the traditional DSS structure. The function of the PCMS is to control user access to the functions of the other components of the DSS. In a test DSS they have built the PCMS using ES technology. Their conclusion is that the use of ES technology in DSS improves the user system interface and functionality of components of specific DSS.

Goul (1992) reflects on the AI emerging as a reference discipline in IS since the first Special Issue of Decision Sciences on ES and DSS was published in 1987. The early research covers a first generation of intelligent DSS using rule-based ES and already opened up trajectories toward intelligent DSS that use, for example, neural networks, genetic algorithms or fuzzy logic.

Research on the application of AI techniques in decision support and recent advances in AI have led to the development of Intelligent Decision Support Systems (IDSS). In order to enhance the capabilities of decision makers IDSS use expert systems technologies. Examples of IDSS are text analytics and mining-based DSS, ambient intelligence and internet of things (IoT)-based DSS, biometrics-based DSS, recommender, advisory and expert systems. They further include GA-based, fuzzy sets, rough sets-based, intelligent agent-assisted, adaptive, computer vision based, sensory, robotic DSS (Kaklauskas, 2015).

Having explored the early use of Artificial Intelligence (AI) techniques in this introductory section, we will now review Intelligent Decision Support Systems (IDSS) (Section 2). Next we specifically analyse research on model selection and identify important characteristics. Based on this analysis we suggest an framework and architecture for a Context-aware Intelligent Model Selection System (CIMSS) (Section 3). Section 4 concludes with further suggestions for future research.

Research on Model Selection

The developments in model management draw heavily upon artificial intelligence concepts and techniques to improve the representation of models as well as the elicitation of models (Konsynski and Sprague, 1986). One comprehensive approach to modelling has been proposed by Geoffrion (1992a, 1992b) with his Structured Modelling approach. Structured Modelling aims at providing a formal mathematical framework and a computer-based environment for creating, representing and manipulating a variety of models. It uses a hierarchically organized, partitioned, and attributed acyclic graph to represent models. The framework has three levels: elemental structure, generic structure and modular structure. Structured Modelling finds its limitations in particular in the complexity of the schema representation which impedes a wider usage. Further, it is not well suited beyond static models, e.g. for the representation of dynamic events and processes.

There have been attempts to develop tools that retrieve models, formally represent and codify models and appropriately match models with problems. Konsynski and Sprague (1986) consider that the area of identification and elicitation of models has been neglected in model management and indicate that there are great opportunities for unique approaches to this elicitation process. Their suggestion is that the approach used for model elicitation in expert systems should also be examined for use in model management systems. They conclude that the techniques and approaches from AI will supply a third resource besides data base and model base by adding knowledge base and a knowledge base management system. This will help less structured problems.

Dutta (1996) emphasized that model selection is an important activity often requiring specialized skills and claims that any AI-based method which can capture this expertise would be helpful to this task. Gnanendran and Sundarraj (2006) have shown that changing the representation of a model can have a dramatic impact on algorithmic performance.

Three levels of model selection capability have been identified by Bonczek et al. (1982): Level 1 - the user procedurally specifies the models algorithm, which can be quite cumbersome if the models are large or complex. Level 2 - the user who is familiar with a selection of models selects one of them for execution where various models are available but it is left to the user to select one of them. This method assumes that the user has knowledge to evaluate the advantages and disadvantages of each model and can identify the most appropriate one. Level 3 - the user gives the system a problem description and the system selects or composes a model suiting the user.

An example of a system that comes close to level three is the one by Sivasankaran and Jarke (1985). It composes models in the actuarial sciences from a library of stored formulas using AI techniques to search a relational structure representing a mapping from input to output attributes.

The integration of DBMS with ES to produce expert data base management systems suggests that there may also be a productive integration of causal decision models with expert systems. Blanning (1987) suggests a framework for this integration and three areas where the integration can occur (1) an expert system that helps users to construct models and then interpret their results (2) an expert system along with or in place of a causal model and (3) using AI techniques including expert systems to translate and execute user queries to a model management system. In this there are two further aspects that will be of importance: First, if the query is in natural language then the system must translate the query into an unambiguous form for execution as in the case of natural language query processors. Second, once the MMS has interpreted the query the MMS must select the model or models to prepare a response and then execute the same. If there is only one model to select it is not difficult but if there is more than one model then aspects of sequence of the models have to be considered. Blanning (1993) has summarized these aspects in an overview of model management systems.

One attractive solution to some of the problems faced by managers has been postulated by Drud (1988). He suggests a system that accepts a user friendly representation of a model, translates it into a form acceptable to a solution algorithm, invokes the algorithm and translates the output back into a form that can be interpreted by the modeler. Drud views the solver or solution algorithm as merely a utility tool with which the modelling system communicates. He discusses the setup of external interfaces to subroutine systems and to self-contained systems as implemented in GAMS.

An expert system that will emulate expert knowledge representation (KR) schema for LP and the methods experts use to manipulate the KR schema is described by Sklar (1990). Sklar states that such a system would free the user from the tedium of translating the problem into the format required by the LP and allow him/her to focus on the problem. This in turn would encourage wider use of LP models. Sklar et al. report that experts use different kinds of knowledge in building LP formulations/selecting type of LP to use for a particular situation namely (a) syntactic LP knowledge that is rules for building grammatically valid LP constraints and objective functions (b) semantic LP formulation knowledge that is rules pertaining to interrelationships between different parts of an LP formulation including information necessary to translate inputs into problem parts as well as information required to connect problem parts like flow capacity or inventory balance constraints (c) semantic LP domain knowledge specific domain knowledge in areas like production management and (d) semantic world knowledge that is general knowledge of the world. Sklar (1990) suggests a combination of production rules, inheritance networks and frame representation since these approaches have the potential ability to store the syntactic, semantic and procedural knowledge required for LP formulation/selection. His research shows that such a hybrid scheme is appropriate and further states that combining the verbal elicitation techniques with working through LP formulations to be a useful knowledge acquisition approach.

An approach that incorporates machine learning to acquire model manipulation/selection knowledge stored in the form of a schema and to refine the schema over a period of time is suggested by Shaw et al. (1988). They suggest the creation of a model selection heuristic adaptive to the decision support system environment. That is when there is more than one way to solve a given problem (as in the case of forecasting we have regression, moving average, exponential smoothing, Box-Jenkins and others) the user has to select the best model or the MMS can choose among the alternatives based on an utility function which is based on past performance and human experts experiences. Whenever the system selects a model the system should give reasons for selecting it over other models. This is achieved by applying the credit assignment technique [35] which determines the steps in the problem solving process that are desirable and assigns credits and those that are undesirable are assigned blames. In model selection, desirable models are strengthened as they are used and undesirable models are weakened. Thus the system dynamically refines the evaluation function of model selection. The objective was to make model selection adaptive to the user's preferences. They have used the concepts of a probabilistic learning system (PLS) to develop the dynamic evaluation function which can be incrementally modified.

The concept of selection of the best model or the best combination of the models has been used by Collopy et al. (1992) in the forecasting arena. They used procedures that applied forecasting expertise and domain specific knowledge to produce forecasts according to the features of the data. They developed a rule base that drew upon protocol analysis of experts in forecasting and combined forecasts from different extrapolation methods according to rules using eighteen features of the time series data. They found that the forecasts produced by this method were more accurate than equally weighted combined forecasts when the trends were significant, uncertainty was low, stability was high and good domain expertise was available. This approach made the system more user friendly, the manager need not know the details of the model, he/she just gives the system the data and answers questions that are domain specific.

Zahedi (1990) introduces the concept of 'meta-OR' for formalizing the qualitative knowledge embedded in the practical applications of MS/OR techniques. Zahedi's application of this concept in the area of Integer Programming (IP) applications shows that codifying the qualitative knowledge of the application process could prove helpful in transferring expertise on OR applications. Zahedi suggests that knowledge of the theoretical aspects of the problem as well as the practical/experiential facts about the problem should be encoded into the form of rules so that they can aid in model selection.

Mookerjee and Chaturvedi (1993) draw upon developments in AI and develop a blackboard control architecture for model selection and sequencing with three elements: (1) a central blackboard that records the necessary information for problem solving, (2) the knowledge sources consisting of models, a database and a user, and (3) an aisle controller, i.e. scheduler, which performs the crucial task of controlling the sequence in which models are used to solve problems.

Artificial Neural Networks (ANN) have been proposed for DSS by Delen and Sharda (2008) and for forecasting model selection by Venkatachalam and Sohl (1999). Lee and Huh (2006) have developed a model-solver integration framework for autonomous and intelligent model solution that will also allow us to fully automate the solver selection process in the future. Further, advanced analytics has been applied by Kumar et al. [25] to create a framework specifically for a Model Selection Management System.

Context-aware Intelligent Model Selection System Framework and Architecture

Context-aware computing refers to the ability of a system to sense and dynamically adapt to changes in its environment, such as physical context, computational context, and user context/tasks, e.g. user location and orientation, depending on the kind of system (Bettini et al, 2010). More generally, Gartner (2016) defines it as a style of computing in which situational and environmental information about people, places and things is used to anticipate immediate needs and proactively offer enriched, situation-aware and usable content, functions and experiences.

Hong et al. have provided an extensive literature review and classification on context-aware systems (Hong et al, 2009) Feng et al. (2009) have developed a model specifically for situation awareness in decision support, Ngai et al. (2012) have designed and developed a context-aware decision support system, and Kwong (2006) has explored potential roles of context-aware computing technology in optimization-based intelligent decision-making.

A unified architecture for an intelligent IDSS is presented by Teng et al. (1988). It consists of a central intelligence manager (CIM) in the architecture which, in turn, comprises an inference engine (a gatekeeper) and an intelligent supervisor (channeling the communication inside the IDSS). In order to facilitate knowledge representation a knowledge-acquisition subsystem has also been incorporated in the architecture.

Phillips-Wren et al. (2006) propose a unifying architecture for the evaluation of IDSS. Lu et al. (2000) have proposed a guidance framework for designing intelligent systems to help a typical decision-maker in selecting the most appropriate method for solving various multi-objective decision-making problems.

Levashova and Smirnov (2014) propose a methodology for context-aware DSS based on integration of models. The models not only describe functional capabilities of the system as it is used but they are also used specify requirements for information and knowledge from the perspective of the system. Comparing these requirements with the user requirements and restrictions helps to obtain the functional capabilities available to the user.

Model Selection in itself is a vast field that has been neglected in model management and there are great opportunities for unique approaches in this area. The literature survey of the different approaches in model selection resulted in identification of key problems:

(a) domain specific approaches

(b) paradigm specific approaches

(c) lack of contextual awareness

(d) numerous approaches to model representation resulting in impedance mismatches

(e) lack of integrability and incompatibility between models – the data they use and the solvers they use

(f) very little support for the evolution of models as the problem changes

(g) redundancy and inconsistency of models and their representation

These strengths and weaknesses identified in the review of literature has helped us to synthesize a system that has the following characteristics.

1. The use of AI techniques especially expert systems/rule based systems in model selection is proving to be fruitful and is suggested as the most promising tool to design model selection systems.
2. The rule base or knowledge base that will be used for model selection should be domain specific. When we speak of domain here, there are two kinds of domain that are possible (a) MS/OR Model domain - like Inventory models, Forecasting models, Production Scheduling models, etc. and (b) Application domain - within say Inventory there will be further domains like inventory models for spares parts and inventory models for consumables etc.

   Figure 1 below illustrates our conceptual framework for a purpose driven problem oriented model selection approach. This approach keeps in mind the fact that the final decision maker and the modeler or model builder could be quite different. And each of them could have a different purpose and problem for whose contexts they have modelled and/or selected and/or integrated from a collection of models.

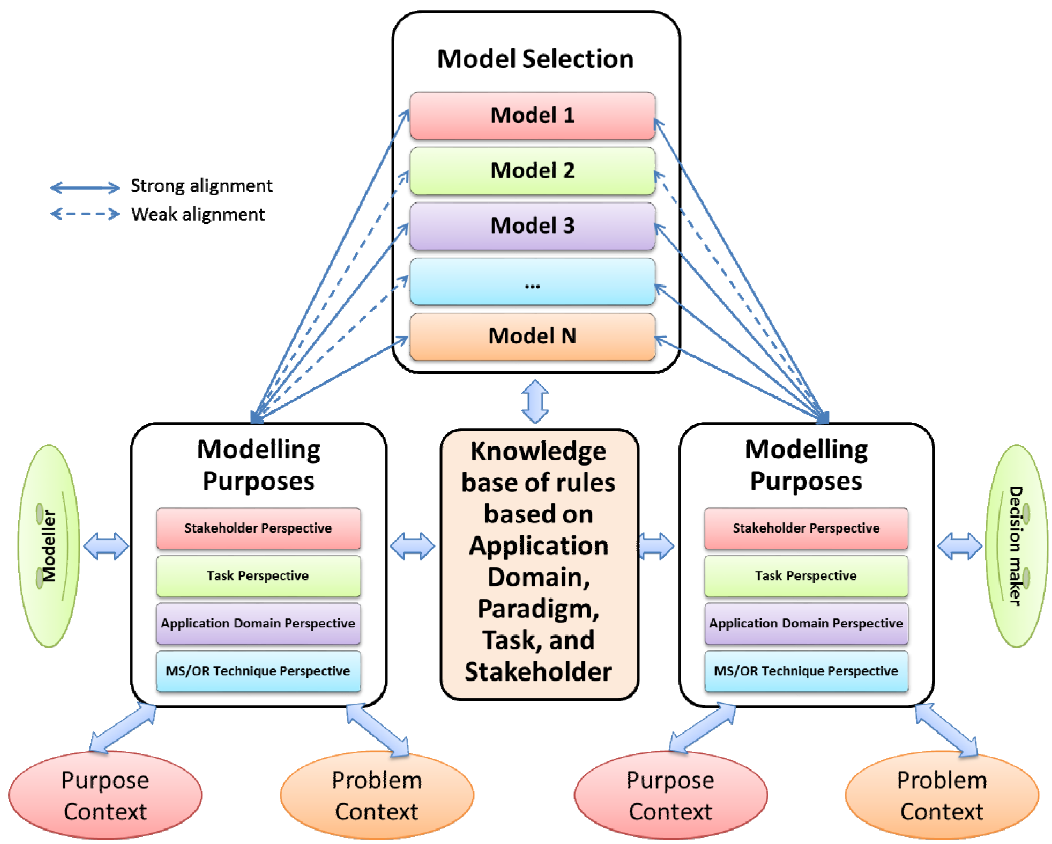

Fig 1. Purpose-driven Problem-oriented Domain and Paradigm Dependent Rule-based Model Selection Framework

We also acknowledge that there could be many different perspectives such as that of the stakeholders in the decision or problem, the task, the application domain and the MS/OR technique or paradigm. Each of these perspectives have associated with them rules that define or narrow or broaden the potential selection of models.

3. Whatever the model representation schema may be (whether relational or frame or using semantic inheritance network or others) there will always be a model selection component which will preferably be rule based.
4. The model selection component should be able to interact with the user, gather information about the problem at hand and - based on this interaction - select one model or a sequence of models for the user from a set of model candidates.
5. The knowledge required to populate this rule based system will be of three types:
   a) MS/OR technique that could be culled from MS/OR scientists through the use of Sklar et al. (1990) context focusing sessions. These could be encoded in the form of standard or fuzzy logic rules that allow the selection of paradigm-specific model(s).
   b) application domain that could be extracted from application domain experts through a similar context focusing session. Here again rules could be created that encompasses the selection of the model(s) appropriate to the domain.
   c) desirable and undesirable models for specific situations. This could be built/refined as the model selection system is used.

   Another method for populating the knowledge base is by using the concept of 'meta-OR' for formalizing the qualitative knowledge embedded in the practical applications of MS/OR techniques.
6. Once the model has been selected by the model selection system there should be another system that should execute the model this could be an off-the-shelf package like GAMS or SPSS or could be a custom built modelbase.
7. Once the models are executed there should exist another system that will present the results to the user in a way that is easily understood by a MS/OR naive person.

The characteristics suggest an architecture as depicted in Figure 2. The architecture in addition to the traditional DSS structure has a Knowledge base management system that uses the three kinds of knowledge discussed above and a Rule and AI based Model Selection System as part of the user interface. Furthermore, the system considers three critical contexts: organizational, resource, and environmental.

This system with the characteristics discussed above should be validated by selecting a domain like forecasting models or inventory models or LP models and conducting context focusing sessions with MS/OR expert in the domain and deriving rules for usage of the models. Surveying past systems developed in application areas within this domain and encoding the qualitative knowledge in the form of rules is the next step. Designing a prototype with an architecture as suggested in Figure 2 and applying the prototype on a few representative sample of users in the application domain and in the MS/OR domain is the next step. Obtaining their feedback, correcting lacunas in the prototype and applying the new prototype across a wider cross-section of users would validate the approach.

Conclusions

This paper explored the early use of Artificial Intelligence (AI) techniques, reviewed Intelligent Decision Support Systems (IDSS). Based on an analysis of research on model selection we identified important characteristics and suggested (a) a framework to under the purpose and problem contexts within which model selection could occur (b) we also looked at the different perspectives such as stakeholders, task, domain, and paradigm (c) we proposed that these perspectives and contexts could be encoded in the form of rules that could help us in selection of appropriate model(s) for the task and (d) finally we proposed an architecture for a Context-aware Intelligent Model Selection System (CIMSS). Guidance for future research can be found in a number of questions posed by Krishnan and Chari (2000). Research in order to specifically address acceptance issues of model-driven DSS may include behavioral and technical questions as outlined by Power and Sharda (2007).

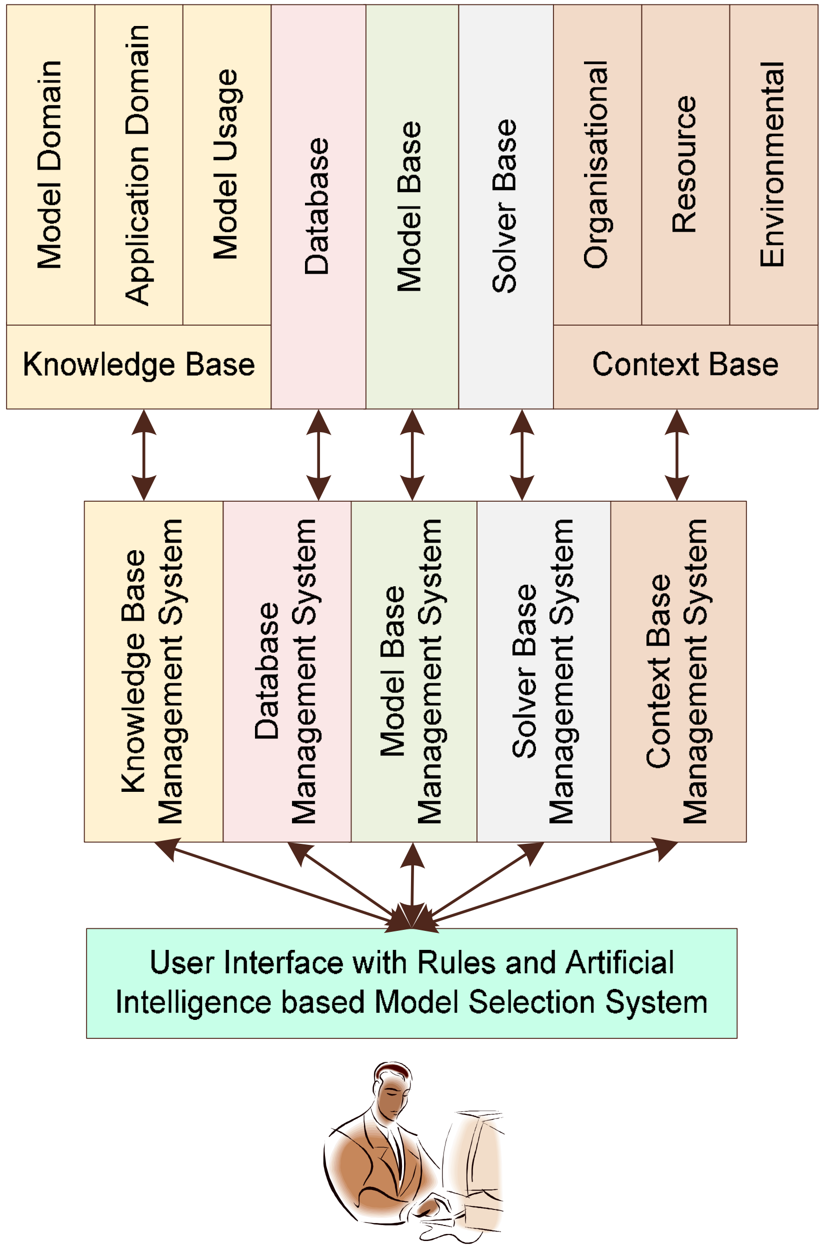

Fig 2. Context-aware Intelligent Model Selection System Architecture

A main focus of future research will be 'next generation model management' which comprises Enterprise Model Management (Sundaram and Wolf, 2009; Goul and Corral, 2007), Service-Based Model Management, Leveraging XML and Data Warehouse/OLAP Technology, Model Management as Knowledge Management, Search-Based Model Management, Computational Model Management. Generic model management as suggested by Melnik (2004) and Bernstein and Melnik (2007) may further ease the use of models for decision makers. One of the most interesting questions for future is whether model selection and model management should be fully automated in DSS and how this can be facilitated with the help of artificial intelligence. Decision makers would not need to have as highly sophisticated model expertise to use such DSS as if they had to select the model manually. However, the challenge is then shifted from possibly applying a wrong or suboptimal model to a wrong interpretation of results.

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