AN INTEGRATED FRAMEWORK OF DESIGNING A DECISION SUPPORT SYSTEM FOR ENGINEERING PREDICTIVE MAINTENANCE

Daniela Borissova, Ivan Mustakerov

Abstract: *The paper describes a framework of decision support system for engineering predictive maintenance for civil engineering. The proposed framework integrates traditional decision support system with the advances of expert system. While the traditional decision support system constitutes data management, decision methodology and user interface the advances of expert system embrace symbolic reasoning and explanation capabilities. That assists decision maker in making strategic decisions by presenting information and interpretations for various alternatives. The essence of the proposed integrate framework of decision support system is the ability to incorporate actual information from structure health monitoring and structure health modeling modules with knowledge management module in a structure of health management module. The data flow diagrams are used to define how data is processed and stored. They also show the points of data entry and exit and are important tool assisting in building a logical model of the designed system. All of these contributed the predictive maintenance enhancement by using of advantages decision support system together with the capabilities of expert system.*

Keywords: *decision support system, knowledge management, expert system, predictive maintenance.*

ACM Classification Keywords: *H.4.2 [Information systems applications]: Types of systems – Decision support; I.2.5 [Artificial intelligence]: Programming Languages and Software – Expert system tools and techniques.*

Introduction

Nowadays, production assets are under constant pressure for reducing operating costs, enhancing reliability of the equipments, and improving the quality of the product. Intelligent fault diagnosis and failure prognosis is a cutting-edge direction involving interdisciplinary methods. It requires understanding of the physics of failure mechanisms for condition-based maintenance in materials and structures and also presents strategies to detect faults or incipient failures. The goal is to provide a framework of decision support systems (DSS) for engineering predictive maintenance helping to take intelligent decisions. Predictive maintenance is the combining of various measurements or data-sources to establish patterns that allow the state of an engineering system to be predicted. The purpose of predictive maintenance is to establish criteria upon which planned maintenance can be carried out before a failure or unexpected stoppage. Predictive maintenance strategies are very efficient in mechanical-failure modes, when failure probability increases with time, and one or more condition-monitoring techniques can predict the failure before breakage [Gilabert & Arnaiz, 2006]. Actuators and sensors placement require specific knowledge to perform the constraints as it is demonstrated [Flynn & Todd, 2010]. The problem of optimal sensor placement considers not only to find the best sensors location for a given task but also to estimate the required number of sensors for the best sensor performance [Borissova, et al., 2012]. Optimal location defining and optimal numbers of sensors determining are two separate problems. The knowledge and experience of engineers are combined with signal processing for the proper solving of optimal sensors locations problem. Designers and end-users of structures know where are the critical machinery areas which need to be analyzed, controlled or monitored. Then an intelligent signal processing could help for the best sensor locations.

The problem of optimal number of sensors relies very much on advanced signal processing techniques [Staszewski & Worden, 2001]. From the signal processing point of view, optimal sensor location is optimization and/or selection problem.

Condition-based maintenance is a decision-making strategy to enable real-time diagnosis of impending failures and prognosis of future equipment health, where the decision to perform maintenance is reached by observing the "condition" of the system and its components [Peng et al., 2010]. Condition-based maintenance method is used to reduce the uncertainty of maintenance activities, and is carried out according to the need indicated by the equipment condition. The existence of indicative prognostic parameters can be detected and used to quantify possible failure of equipment before it actually occurs. In maintenance, common problems of equipment are aging and deterioration. The trend of the deterioration of critical components can also be identified through a trend analysis of the equipment condition data. Maintenance decisions depend very much on actual measured abnormalities and incipient faults, and the prediction of the trend of equipment deterioration [Yam et al., 2001]. The condition-based maintenance is conceived to detect the onset of a failure, avoiding critical damages of high cost components before they might happen, thus reducing overall maintenance costs. Possible faults are detected by monitoring representative parameters by signal analysis techniques and comparing signals during normal and abnormal conditions [Velarde-Suarez et al., 2006; Charbonnier et al., 2005]. Also, the methods of case-based reasoning can be applied in units of analysis of the problem situation, search for solutions, learning, adaptation and modification, modeling and forecasting [Eremeev & Varshavskiy, 2008].

The main idea of predictive engineering maintenance is to monitor the health of critical machine components during operation and support the maintenance decisions based on the conditions estimation. The aim of current paper is to provide an integrate framework for development of a new generation of decision support systems by providing tools and methods for a better integration of knowledge management in an evolving environment. The main interest lies not only in improved data analysis, but also in better formalization and use of diagnosis for the goal of engineering predictive maintenance.

Problem Description

The most effective predictive maintenance programs trend to looking for signs of early failure, allowing the equipment to be repaired at minimal cost and down time. In order to best utilize trend analysis, data must be available on a regular basis. Obviously, the more frequently the sampling is performed the more accurate the analysis becomes. Diagnostic reports from the DSS on the condition of the machinery assist maintenance personnel in making critical decisions regarding equipment health conditions. DSS as computer-based information system supports business or organizational decision-making activities. DSS aid in problem solving by allowing for manipulation of data and models whereas expert systems allow experts to "teach" computers about their field so that the system may support more of the decision making process for less expert decision makers. From maintenance point of view, a properly designed DSS should integrate not only decision making process where human user is required to weigh all the factors in making a decision but also the capabilities of expert system which acquire knowledge from an expert and apply a large but standard set of probability based rules to make a decision in a specific problem setting. Such predictive maintenance software-based system will help decision makers compile useful information from monitoring, documents, personal knowledge, and models to identify and solve problems and to make the most appropriate decision.

Because decision-making is based on many different considerations, decision support systems belong to a multidisciplinary environment, including among others database research, artificial intelligence, human-computer interaction, simulation methods, and software engineering. Combining the capabilities of DSS (contain equations that the system uses to solve problems or update reports immediately, and the users makes the final decisions on the basis of the information) with advantages of expert system (works from a much larger set of modeling rules, uses concepts from artificial intelligence to process and store the knowledge base and scans base to suggest a final decision through inference) an integrated framework of DSS for metallurgical engineering predictive maintenance is proposed.

General Context of the DSS Conception

Decision support systems represent a class of computer based information systems, including the knowledge based systems that support decision making in respect of various activities. Properly designed DSS are interactive software system designed to facilitate the decision maker to use information from data, documents, personal knowledge and/or models to identify and solve problems and make decisions. A DSS is a way to model data and make quality decisions based on it. DSS support decision maker, when scrolling through large amounts of data and the choice between different alternatives. Systems for decision support have a certain structure, but in fact the data and decisions based on them are constantly changing. The key to decision support systems is data collection; analysis and structuring of data collected and determines the best decision or strategy as a result of this analysis. Usually it does not matter whether computers, databases or people are involved, this is a process of collecting raw or unstructured data, which are used to decision making.

Types of Decision Support Systems

Concerning the relationship between users and applications, DSS can be divided into three categories – passive DSS, active DSS and proactive DSS as shown on Fig. 1 [Kwon et al., 2005].

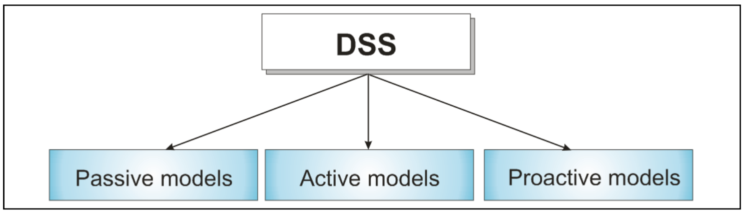

Figure 1. DSS models based on the relationship with decision maker and his preferences

The passive models of DSS only collect data and organize it effectively and do not provide specific solutions, i.e. they only show the collected data. Active decision support systems process data and clearly show solutions based on that data. Although there are many systems that are able to be active, in many organizations will be difficult to believe in a computer model without human intervention. The third category is proactive DSS, which known as ubiquitous computing technology-based DSS which contains decision making and context aware functionalities. They combine the human element and computer components to work together to get the best possible solution.

While the above DSS models take into account the interaction with the user, another popular DSS model consider the way of support (Fig. 2) [Kwon et al., 2005].

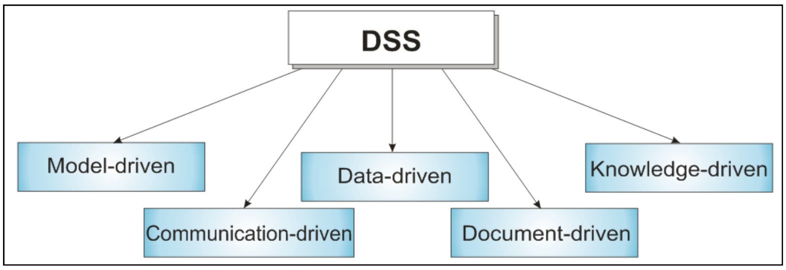

Figure 2. DSS models, based on the way of support

Model-driven DSS is complex systems that help decision maker to analyze or choose between different options. They use algebraic, decision analytic, simulation, and optimization models to provide decision support. Communication-driven DSS enhances decision-making by network and Internet technologies to provide environment for group decision making. Data-driven DSS emphasize on data collection and their manipulation for particular decision maker needs satisfying. They include a database designed to store data in such a way as to allow for its querying and analysis by users. Document-driven DSS uses a variety of documents such as electronics spreadsheet documents and database record for information processing and strategies defining. Knowledge-driven DSS use specific rules coded in computerized expert systems to support the decision maker.

Decision Making Process

According to Baker et al. [Baker et al., 2001], decision making should start with the identification of the decision maker(s) and stakeholder(s) in the decision, reducing the possible disagreement about problem definition, requirements, goals and criteria. Then, a general decision making process can be divided into the following steps:

- Problem definition – the main reasons identification as limiting assumptions, system and all stakeholders. The aim is to convey the essence in a clear sentence that describes both the initial conditions and desired conditions. The formulation of the problem, however, must be short and clearly expressed in writing and agreed by all decision makers;
- Requirements determination – description the requirements that the solution to the problem must meet. In mathematical form, these requirements are constraints describing the set of possible (admissible) solutions. Even if there are subjective evaluations on the next steps it is required specifications in precise quantitative form;
- Definition of objectives – general statements of intent and desired values, i.e. establish the goals that solving the problem should accomplish. In mathematical form, they are functions, as opposed to requirements that are constraints. The objectives can be conflicting, but it is natural to solve practical problems;
- Identification of alternatives – different approaches to change the initial state to desired state of the process. If the number of possible alternatives is finite, they can be checked one by one, if eligible. If the number of possible alternatives is infinite, the set of alternatives is seen as a set of solutions satisfying the requirements expressed mathematically as restrictions;
- Determination of criteria – needed to define the measures of objectives to estimate how each alternative achieves the objectives. The criteria are usually based on objectives but sometimes it is possible to have more than one criterion for some objective;

- Select a tool for decision making – different tools that can support the decision maker. Choosing the appropriate instrument depends on the specifics of the problem and the objectives of the decision maker;
- Assessment of alternatives against the criteria – alternative evaluation by appraising it against the criteria;
- Solution verification – the proposed solutions are compared against the goals and corrective actions are taken if needed.

Identifying and choosing alternatives based on the values and preferences of the decision maker are realize as a result of decision making process. These basics steps will be incorporate in the proposed integrated framework of DSS for engineering predictive maintenance.

Conceptual Model for Decision Support System

In the context of decision support systems, DSS are often an agglomeration of different techniques and methods that aim at fulfilling a function to support the decision maker. DSS structure consists in many modules and sub-modules depending on the flow of collecting and processing data. Different authors identify different components of DSS. Three fundamental components of DSS as database management system, model-base management system and dialog generation and management system are identified in [Sprague & Carlson, 1982]. According to [Power, 2002], DSS is described by four major components: user interface, database, model and analytical tools, and DSS architecture and network. Another generalized architecture [Marakas, 1999] with five distinct parts: data management system, model management system, knowledge engine, user interface, and user(s) is proposed. Taking into account the above considerations a conceptual architecture of typical DSS is shown on Fig. 3.

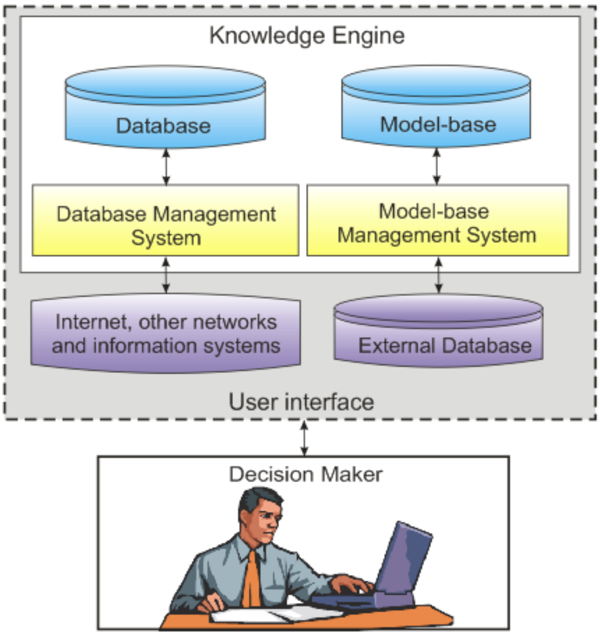

Figure 3. Architecture of conceptual DSS model

The DSS dialogue requires tradeoffs between simplicity and flexibility. Therefore, the user interface of DSS should facilitate decision makers to have easy access, manipulation and usage of common decision domain terms with all aspects of communication between the user and the DSS. Decision maker accesses database and model-base through database management system and model-base management system. They enable the user to build a system to assist in making a particular type of decision. External database access allows the DSS to examine the existing outside information, while connections to other network and information systems provide access to information external to the organization like World Wide Web.

Different decision strategy could be used to transform initial information to a decision maker point of view. In decision-making process there are various kinds of uncertainty, depending on the reasons for its occurrence. Among the many sources of uncertainty the mainly distinguished incompleteness is the lack of information, fortuitousness, which cannot be predicted. In such problems, optimal strategies approaches for decision making under uncertainty conditions could be more appropriate [Borissova et al., 2011]. Although there is no widely accepted definition of DSS, these systems can integrate a number of decision support technologies (tools), including optimization and simulation models, information systems, data-mining tools, expert or knowledge-based systems, statistical and graphing tools, etc. Nevertheless, there are three fundamental components of DSS architecture that always exist – the database, the model-base (the decision context and user criteria) and the user interface.

An Integrated Framework of Decision Support System for Engineering Predictive Maintenance

The design of a DSS for engineering predictive maintenance starts with choosing of the objectives. The end-user input will help determine the exact objectives, outputs and any additional requirements. The specifics of the predictive maintenance require usage of some monitoring system for engineering critical structural sections. This ensures that appropriate sensors for the requirements of monitoring will be selected and optimally located in such a way that sufficient information can be gathered. Typical predictive maintenance includes methods for data acquiring and information fusion combined with signal processing. In the current paper knowledge management subsystem is proposed as a module in the DSS. It stores and manages knowledge from prior data, human expertise, examples (cases) for the goal of machine learning and case-based reasoning. That module benefits from learned experience and will contribute to intelligent behavior and improved performance based on artificial intelligence. The included inference engine will support the intelligent decisions making about the structure health. The advantages of DSS could be combined with capabilities of expert system into an integrated framework of DSS for civil engineering predictive maintenance. A general framework of such DSS could be compound of four main modules for: structure properties defining and sensors placement, structure health monitoring, structure health modeling and structure health management as it is shown on Fig. 4.

The structure properties defining and sensors placement module provides tools for choice of proper sensors type, number and locations. The proper sensor type is based on structure properties and includes measurement range (sensitivity), frequency range, broadband resolution (noise), temperature range, sensitivity tolerance and size. The knowledge of a structure, past experience or analytical tools as finite element analysis can be used to define the sensors locations. In addition, different fitness function can be used to formulate optimization task, which solution will define optimal sensors locations.

The structure health monitoring module derives directly from routinely collected condition monitoring signals from the sensors and from historical records to produce prediction outputs directly in terms of condition monitoring data. The signal processing of sensor data is one of the most important functions of structural health monitoring systems for goal of predictive maintenance. The results from signal processing are collected in an actual sensor database for additional processing and feature extraction and selection, pattern recognition and information fusion. The external data sources as Internet, other networks and information systems are also used. The collected data are assessable through database management system as aid in the decision making process.

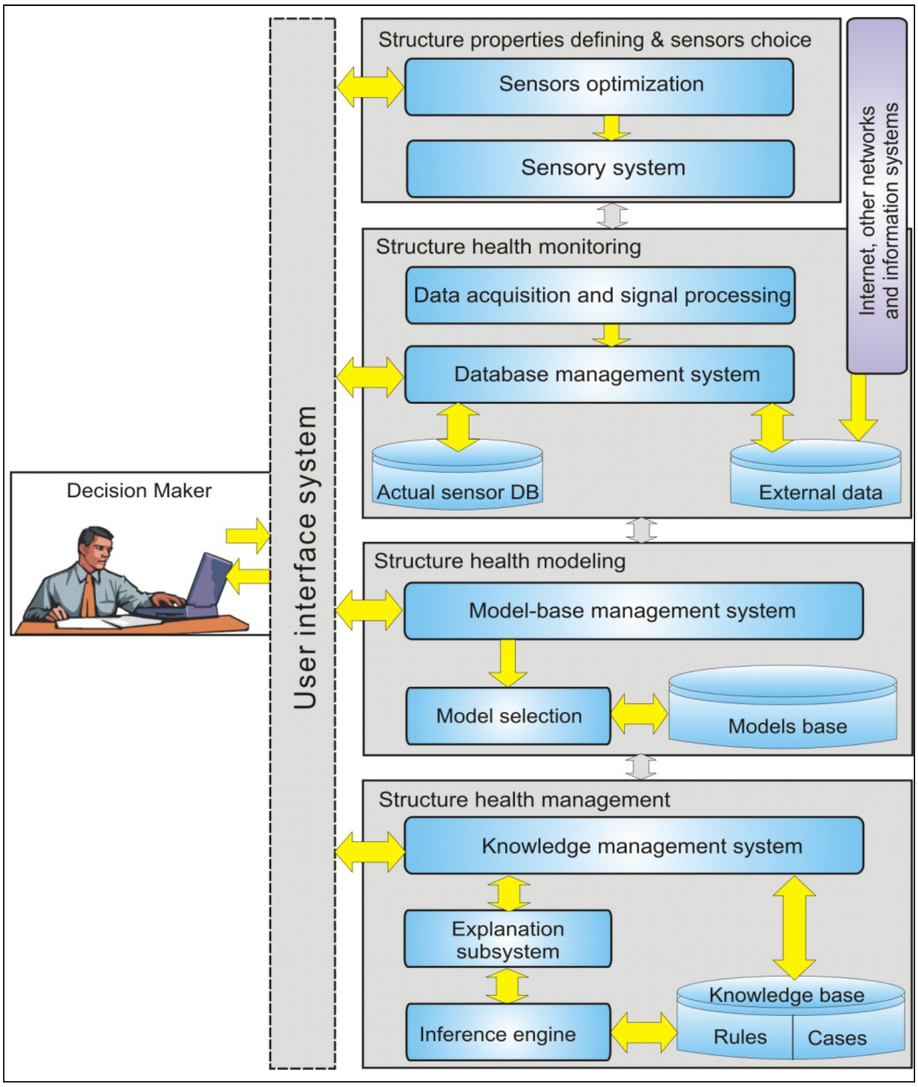

Figure 4. An intergated framework of DSS for engineering predictive maintenance

Other characteristic of proposed DSS is the modeling capability represented by structure health modeling module. Some of models can estimate the time to failure of a machine as well as forecasting the fault condition. The way in which a prognostic model is developed differs therefore from the method for building an explanatory model. The prognostic model is focus on the search for a combination of factors which are as strongly as possible related to the outcome. Accurate prognostic models are based on algorithms that are capable of predicting future component failure rates or performance degradation rates. Development of strategies for assessment prognostic modeling of machinery working life involves various methods including structural system reliability, probabilistic-based life cycle assessment and maintenance, optimization of multiple criteria under uncertainty and integration of monitoring in life cycle management. Combining the advantages of these methods could aid the decision-maker in decision making process for engineering systems diagnostics under uncertainty or incomplete information conditions. A well-designed combination model could combine two or more theories and algorithms to model the system in order to eliminate the disadvantages of each individual theory and utilize the advantages of all combined methods. It should be pointed out, that it is a challenging work to choose appropriate methods and combine them together for modeling.

The engineering predictive maintenance is a specific subject area which is characterized by availability of past information about the possible problems, their diagnosis, assessment of situations and effective solutions. That information can be incorporated in an expert system module used for structure health management to recommend courses of action and decisions. The structure health management module is composed of knowledge management system, knowledge base, inference engine and explanation subsystem. The knowledge management system is responsible for knowledge extraction and storing in a knowledge base in the form of rules. It also interacts with decision maker to show him the results of incorporated inference engine and how these results are obtained through the explanation subsystem. Knowledge extraction conducted primarily during interviews with experts, field visits, service order, manuals, technical documentation and actual operations. During the interview process, conversations were recorded in detail and then transformed into acceptable format for diagnosing rules. Usually, rules are expressed in the form: *IF* condition, *THEN* consequence. The outcomes can be used also to test other conditions/rules, or even add a new fact to the knowledge base. These rules can be specific domain rules or heuristic rules and can be chained together using logical operators. The knowledge consists of concepts, objects, relationships and inference rules.The set of rules constitute the knowledge base. Another part of the knowledge base stores a set of problems and answers needed for case base reasoning. Condition base reasoning solves new problems by retrieving relevant prior cases and adapting them to fit new situations. Condition base reasoning is responsible to find the case that is most closely related to the new problem and present a case's solution as an output, with suitable modifications. Condition base reasoning can be effective even if the knowledge base or domain theory is incomplete. Certain techniques of automated learning, such as explanation-based learning, work well when only a strong domain theory exists, whereas condition base reasoning can use many examples to overcome the gaps in a weak domain theory while still taking advantage of the domain theory. These characteristics of condition base reasoning make it appropriate for diagnosis, prognosis, and predictive maintenance. The inference engine applies the knowledge base to the particular fact of the case under consideration to derive conclusions that can be used by the decision maker. An important feature is the possibility to justify the conclusions by the explanation subsystem. It should answer the questions of type “how the conclusion is reached” or “why the conclusion is reached” or “trace the conclusion” and could be a great help for decision maker to take the solutions about the predictive maintenance activities. The expert system included in the DSS compensates for the user's limitations about some expertise areas. It makes use of all available expert resources to present the most complete picture of the problem possible.

The advantage of proposed integrated framework of DSS contribute to enhance the predictive maintenance taking into account decision maker preference together with the capabilities of expert system by means of collected knowledge to make a decision in a specific problem setting. Therefore, the maintenance decisions rely on not only of decision maker but also on the knowledge of actual sensor data base, model base and rule base knowledge.

Data Flows in the Proposed DSS Framework

An essential step in DSS design process is to describe how the system transforms data. For that goal, the data flow diagrams are used to define how data is processed and stored. They also show the points of data entry and exit and are important tool assisting in building a logical model of the designed system. A generalized data flow diagram of the proposed DSS is shown on Fig. 5.

To describe the logic and the actions on the data through data flow diagram the following basic steps could be distinguished:

- Identifying the main processes and the external data sources and their inputs and outputs;
- Identifying the data flows from the external entities;
- Identifying the processes to perform to generate the input and output data flows;

- Identifying the data stores;
- Connecting the processes and data stores with properly directed data flow;
- Naming each data flow, data store and process.

The interaction between decision maker and DSS start with definition of the structure properties and parameters to be monitored. Type and sensor's locations are defined on the basis of some theoretical investigations as finite element analysis for example, or on the basis of past experience or from external data queries. The theoretical investigations on sensors locations usually lead to large number of sensors. The next step is to minimize sensor's number by optimizing their layout design in term of structural health monitoring. This is realized by optimization tasks solving which are implemented in the first DSS module. The decision maker is responsible to choose optimization criterion and/or acceptable range of data loss from the sensors. The data from the installed sensors is collected and processed. Signal processing of sensors data supplies the actual monitoring data that is stored in actual database and used for structural health monitoring. Statistical process control is another tool aimed at continuously monitoring the common cause system and detecting significant deviations, possibly pointing to special assignable causes.

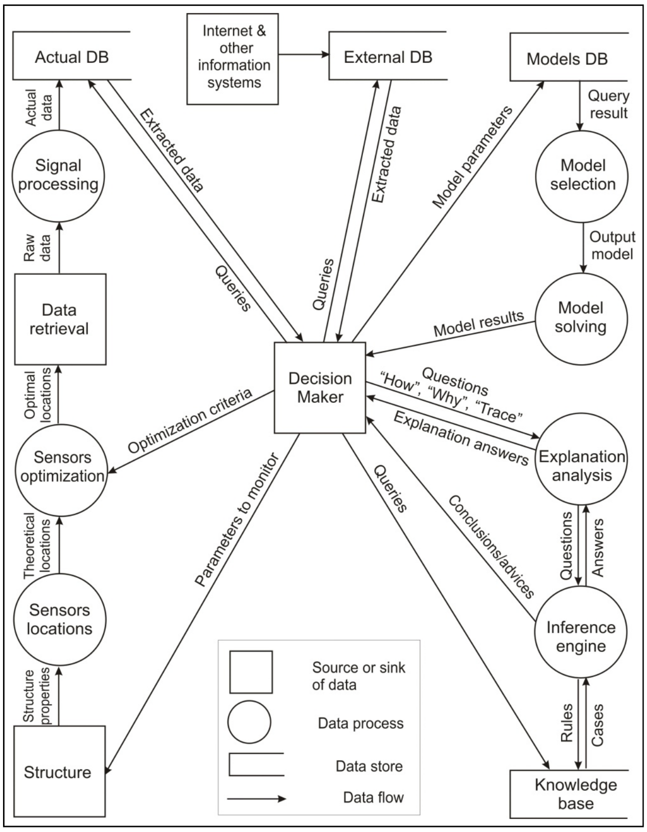

Figure 5. Generalized data flow diagram of the proposed DSS for engineering predictive maintenance

The external data sources as Internet, other networks and information systems are assessable through database external database. This component allows the DSS to examine and use outside experience. Model base is a set of computer decision models similar to database, the only difference is that its stored objects are models. The models in the model base can be strategic, tactical, operational and analytical, etc. The data and parameters provided by decision maker are used to select a model, which is suitable for analyzing a situation. The selected model represents knowledge about a system by means of algebraic, logical, or statistical variables that interact by mathematical functions or logical rules. The mathematical methods analyze and solve the selected model to support decision making. Decision making under uncertainty enhances the above methods with statistical approaches, such as reliability analysis, simulation.

The knowledge in structure health management module is based on "expertise" about a particular domain, understanding of problems within that domain, and "skill" at solving some of these problems. It can suggest or recommend actions to decision maker that will improve fault detection and recovery. A knowledge base consists of descriptions of the elements in the process along with their characteristics, functions, and relationships expressed as a collection of organized facts, rules, and procedures. When certain events occur the decision maker makes queries to knowledge base and inference engine advices what actions to implement. Decision maker can also judge the reasoning behind a conclusion by another query to explanation subsystem.

Summary and Conclusion

In the current paper a framework of decision support system for engineering predictive maintenance is proposed. It integrates traditional decision support system with the advances of expert system. While the traditional decision support system constitutes data management, decision methodology and user interface the advances of expert system embrace symbolic reasoning and explanation capabilities. That assists decision maker in making strategic decisions by presenting information and interpretations for various alternatives. The essence of the proposed decision support system framework is the ability to integrate actual information from structure health monitoring and structure health modeling modules with knowledge management in structure health management module. Therefore, knowledge and decision maker are key factors in maintenance. The maintenance decisions rely on not only of decision maker preferences but also on the knowledge of actual sensor data base, model base and rule base knowledge. So, to enhance the predictive maintenance a decision maker is required to exploit the capabilities of expert system in a defining a maintenance decision.

The proposed framework is tested on a case study at metallurgical company. The sensors optimization module has been developed and numerically tested by using actual data of a sample structure. A number of mixed integer linear programming tasks are formulated and solved with different criteria and restrictions for sensors accuracy deviation. Model database is in the process of completing for high temperature metallurgical objects (fluidized beds, anode refining, etc.). In parallel, expert’s knowledge is in process acquisition for the goal of knowledge base creation.

The benefits of the proposed framework of decision support system for engineering predictive maintenance is in efficiency savings, only carrying out maintenance when necessary but in-time to prevent failures. This can often lead to substantial increases in productivity and decreasing of the maintenance costs.

Acknowledgments

This work has been supported by the National Science Fund of Bulgaria, Ministry of Education, Youth and Science under the Project “Diagnostic and Risk Assessment Predictive Asset Maintenance” No DVU-10-0267/10.

Bibliography

[Baker et al., 2002] D. Baker, D. Bridges, R. Hunter, G. Johnson, J. Krupa, J. Murphy, K. Sorenson, Guidebook to decision-making methods, WSRC-IM-2002-00002, Department of Energy, USA. http://www.dss.dpem.tuc.gr/pdf/Decision%20 Making%20Guidebook_2002.pdf

[Borissova et al., 2011] D. Borissova, I. Mustakerov, V. Grigorova. Engineering systems maintenance by optimal decision making strategies under uncertainty conditions. Problems of Engineering Cybernetics and Robotics, 63(1), 2011, 38-44.

[Borissova et al., 2012] D. Borissova, I. Mustakerov, L. Doukovska. Predictive maintenance sensors placement by combinatorial optimization. International Journal of Electronics and Telecommunications, 58(2), 2012, 153-158.

[Charbonnier et al., 2005] S. Charbonnier, C. Garcia-Beltan, C. Cadet, S. Gentil. Trends extraction and analysis for complex system monitoring and decision support. Engineering Applications of Artificial Intelligence 18, 2005, 21-36.

[Eremeev & Varshavskiy, 2008] Al. Eremeev, P. Varshavskiy. Case-base reasoning method for real time expert diagnostics systems. International Journal "Information Theories and Applications", 15(4), 2008, 119-125.

[Flynn & Todd, 2010] E. B. Flynn, M. D. Todd. A Bayesian approach to optimal sensor placement for structural health monitoring with application to active sensing. Mechanical Systems and Signal Processing, 24, 2010, 891-903.

[Gilabert & Arnaiz, 2006] E. Gilabert, A. Arnaiz. Intelligent automation systems for predictive maintenance: A case study. Robotics and Computer-Integrated Manufacturing, 22, 2006, 543-549.

[Kwon et al., 2005] O. Kwon, K. Yoo, E. Suh. UbiDSS: A proactive intelligent decision support system as an expert system deploying ubiquitous computing technologies. Expert System with Applications, 28(1), 2005, 149-161.

[Marakas, 1999] G. M. Marakas. Decision support systems in the twenty-first century. Upper Saddle River, N. J., Prentice Hall. 1999

[Peng et al., 2010] Y. Peng, M. Dong, M. Jian Zuo. Current status of machine prognostics in condition-based maintenance: a review. International Journal of Advanced Manufacturing Technology, 50, 2010, 297-313.

[Power, 2002] D. J. Power. Decision support systems: concepts and resources for managers. Westport, Conn., Quorum Books. 2002

[Sprague & Carlson, 1982] R. H. Sprague, E. D. Carlson. Building effective decision support systems. Englewood Cliffs, N.J., Prentice-Hall. 1982

[Staszewski & Worden, 2001] W. J. Staszewski, K. Worden. An overview of optimal sensor location methods for damage detection". Smart Structures and Materials, Proceedings of SPIE, 4326, 2001, 179-187.

[Velarde-Suarez et al., 2006] S. Velarde-Suarez, R. Ballesteros-Tajadura, J. Pablo Hurtado-Cruz. A predictive maintenance procedure using pressure and acceleration signals from a centrifugal fan. Applied Acoustics, 67, 2006, 49-61.

[Yam et al., 2001] R. C. M. Yam, P. W. Tse, L. Li, P. Tu. Intelligent Predictive Decision Support System for Condition-Based Maintenance. International Journal of Advanced Manufacturing Technology, 17, 2001, 383-391.

Authors' Information

Ivan Mustakerov *– Associated Professor, Ph.D., Institute of Information and Communication Technologies, Bulgarian Academy of Sciences, Acad. G. Bonchev St., Bl. 2, Sofia 1113, Bulgaria; e-mail: mustakerov@iit.bas.bg*

Major Fields of Scientific Research: Operations research, Engineering systems modeling and design, E-learning systems and tools, Software systems for information processing

Daniela Borissova *– Associated Professor, Ph.D., Institute of Information and Communication Technologies, Bulgarian Academy of Sciences, Acad. G. Bonchev St., Bl. 2, Sofia 1113, Bulgaria; e-mail: dborissova@iit.bas.bg*

Major Fields of Scientific Research: Decision support systems, Software systems for information processing, Modeling and optimization for renewable energy sources and for night vision devices, Web-based applications and Web design.