A Concept of Intelligent e-Maintenance Decision Making System

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***Abstract*—Technological development resulted in increased complexity in both industrial machinery and production systems. The modern industry is increasingly demanded to work at high reliability, low environmental risks, and increased human safety while operating their processes at maximum yield. Therefore, prevention of failures and early detection of incipient machine and systems problems increases the useful operating life of equipment. The paper describes a concept of intelligent e-maintenance decision making system with effective utilization of expert system capability to condition based maintenance policy. The described system's concept incorporates actual condition monitoring information and modeling modules together with knowledge management module and via health assessment module the most appropriate decision making is realized. The intelligent strategy selection is numerically illustrated.**

***Keywords*—condition-based maintenance; e-maintenance concept; expert system; knowledge management; decision making.**

I. INTRODUCTION

E-maintenance vision corresponds to a set of strategic decision rules in coherence to the strategic decision rules of the enterprise [1]. They define not only the main trends of maintenance but also its finality and objectives and consequently they determine the inherent objectives to all the other maintenance processes integrated within the enterprise processes. E-maintenance avoids failure by detecting early deterioration or potential failures involving condition-based maintenance. The condition-based maintenance 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 [2]. 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. Maintenance decisions depend on actual measured abnormalities and incipient faults, and the prediction of the trend of equipment deterioration [3]. 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 [4], [5].

Innovative methods [6], [7] for monitoring and diagnosis and effective allocation of resources to maintain the deteriorating parameters of the object could be used. That is why the ISO 13381-1: 2004 standard prescribes to start with monitoring, followed by diagnostic, prediction and posterior actions [8]:

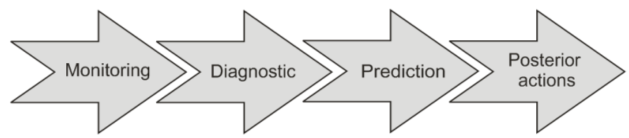

Fig. 1. Stages of ISO 13381-1: 2004 standard

The intelligent systems used in condition-based fault diagnosis can be divided into three categories [9]: rule-based diagnostic systems; case-based diagnostic systems; model-based diagnostic systems. Rule-based diagnostic systems detect and identify incipient faults in accordance with the rules representing the relation of each possible fault with the actual monitored equipment condition. Case-based diagnostic systems use historical records of maintenance cases to provide an interpretation for the actual monitored conditions of the equipment. A model-based diagnostic system uses different mathematical and logical methods to improve diagnostic reasoning based on the structure and properties of the equipment system. A model-based diagnostic system compares the real monitored condition with the model of the object in order to predict the fault behavior.

E-maintenance is the synthesis of two major trends in today's society: the growing importance of maintenance as a key technology and the rapid development of information and communication technology (ICT). ICT and in particular Web and agent-based technologies for data acquisition, data transfer and integration in condition monitoring and maintenance of mechanical systems, is becoming more and more important [10].

E-maintenance basically refers to the integration of the ICT within the maintenance strategy [11], [12]. E-maintenance has been discussed one of the four ways: 1) a maintenance strategy (i.e. a management method), 2) a maintenance plan, 3) a maintenance type or 4) a maintenance support [13]. E-maintenance as maintenance type describes

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replacing traditional maintenance with technological maintenance where predictive maintenance is done with the help of artificially intelligent systems that provide only condition monitoring and predictive prognostic functions. Continuous insight into present and future health of machines and their components, as well as the information flow infrastructure enable the move to e-maintenance based on intelligent prognostics, where maintenance actions are synchronized with the overall operation of the system as well as with the necessary maintenance resources and spare parts [14].

The aim of current paper is to provide an integrated framework for development of a new generation of decision support systems for e-maintenance 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 condition based maintenance.

II. Activities for Condition Based Maintenance

Condition based maintenance is based on the concept of condition monitoring, which means that meaningful measurements of the machine state are taken at regular intervals or even constantly. Monitoring and trending these values can help to anticipate problems and failures, thus responding in time to potential break-downs. The informational basis for the prognosis of future failures can also be obtained from statistical data about the equipment. However, actual condition information yields more accurate prognoses [15]. The global objective of maintenance depend on a mandatory collaboration (inter and intracompany processes integration), mandatory synchronization of knowledge between all the objects–actors–systems involved in the maintenance process all along the various phases of the product life cycle (human and/or automated actors) [1].

The key objective of conditional monitoring is to convert available data into useful information. This requires the ability to collect and evaluate data, analytical tools to evaluate and select the most cost-effective alternative strategies on maintenance management. The technological advances made in information management have made comprehensive maintenance management a feasible goal.

The most effective predictive maintenance programs trend to looking for signs of early failure, allowing the equipment to be repaired at minimal cost and downtime. 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 decision support system (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 assist in problem solving by allowing for manipulation of data and models whereas expert systems allow experts to “teach” computers about their expertise 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.

III. Concept of Decision Making

The decision support systems are intended to enhance individual decision making by providing easier access to problem recognition, problem structure, information management, statistical tools, and the application of knowledge. Such a system is designed to enable the easier and faster generation of alternatives, and to increase the awareness of deficiencies in the decision-making process. It can help the decision maker to make more effective and efficient decisions in complex situations. In the context of decision support systems, different techniques and methods are aggregated to fulfill the function of support the decision maker. DSS structure consists of many 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 [16]. According to [17], DSS is described by four major components: user interface, database, model and analytical tools, and DSS architecture and network. Another generalized architecture [18] describes five distinct parts: data management system, model management system, knowledge engine, user interface, and user(s). Taking into account the above considerations a generalized architecture of DSS is considered as shown in Fig. 2. 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.

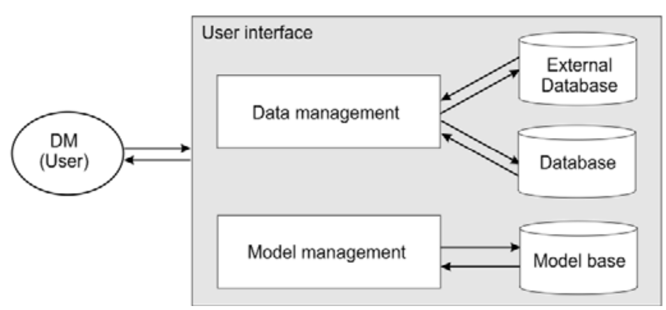

Fig. 2. Generalized architecture of DSS

IV. Expert Systems Architecture in Respect of Condition-Based Maintenance

Knowledge engineering is the interface between the human experts and the expert system. In this kind of information systems the knowledge base is separated from the inference engine, commonly known as the control mechanism, which controls the system when it searches its knowledge base in a dynamic environment (Fig. 3) [19].

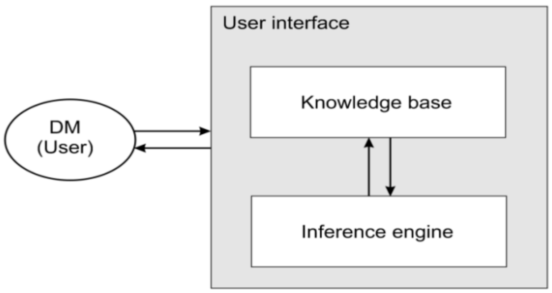

Fig. 3. Generalized architecture of expert system

Knowledge base contains the domain knowledge which is used by the inference engine to draw conclusions. The inference engine is the generic control mechanism that applies the axiomatic knowledge to the task-specific data to arrive at some conclusion. When a user supplies facts or relevant information of query to the expert system he receives advice or expertise in response. That is given the facts it uses the inference engine which in turn uses the knowledge base to infer the solution.

Expert systems can be easily integrated with other programs and databases in order to solve specific problems. However, failure models are difficult to implement in practice, since in many situations failure data are lacking. Over the years, a movement from basic failure models to a more complex one's is done. Today, researchers tackle maintenance management activities from different perspectives, since maintenance plans, condition monitoring techniques and so on, are dependent on the type of the particular equipment.

V. Concept of Intelligent e-Maintenance DSS

E-maintenance intelligent system aims to recommend maintenance actions is based on information collected through condition monitoring – data acquisition, data processing and maintenance decision-making. That means to obtain relevant data to equipment's health; to analyze collected data and to recommend efficient maintenance policies, based on data acquired and processed in previous steps. Collected data via e-maintenance program represent the measurements dealing with the health condition of the physical machine (like vibration data). Condition monitoring is suitable for engineering equipment management since it is able to identify potential failure symptoms and suggest actions before any operational interruptions occur. Conditions of machines can be investigated through various tests and then decision has to be made whether the machine should be repaired or replaced or decide whether further in-depth test is needed. The first step in data processing is cleaning data so that it can be used for efficient analysis and modelling. With respect to condition monitoring data, errors may be caused by the sensor itself, whereupon sensor fault isolation is the best solution. Once data are cleaned, the next step is data analysis. Maintenance decision-support is the last step of e-maintenance. Diagnostics and prognostics are the two main techniques used to perform efficient maintenance policies and decision-making. Within diagnostics, several statistical approaches have been developed, as well as artificial intelligence approach - a computational model that imitates the human brain structure, and model-based approaches.

The main objective of e-maintenance system is to assess machine condition and predict any impending failure, through data acquisition and the act trending the results. Potential problems can be identified through monitoring, comparing its actual performance with design capacity. Combining the data and knowledge from different sources allow maximizing the useful content of the information. The integration of condition based maintenance technologies in e-maintenance system assist the users in automation the maintenance process from point of alert to completion of the maintenance work order. Using proper e-maintenance platform can facilitate analysis and accelerate decision-making.

The concept of intelligent e-maintenance decision making system is realized via 4 basic layers as shown on Fig. 4.

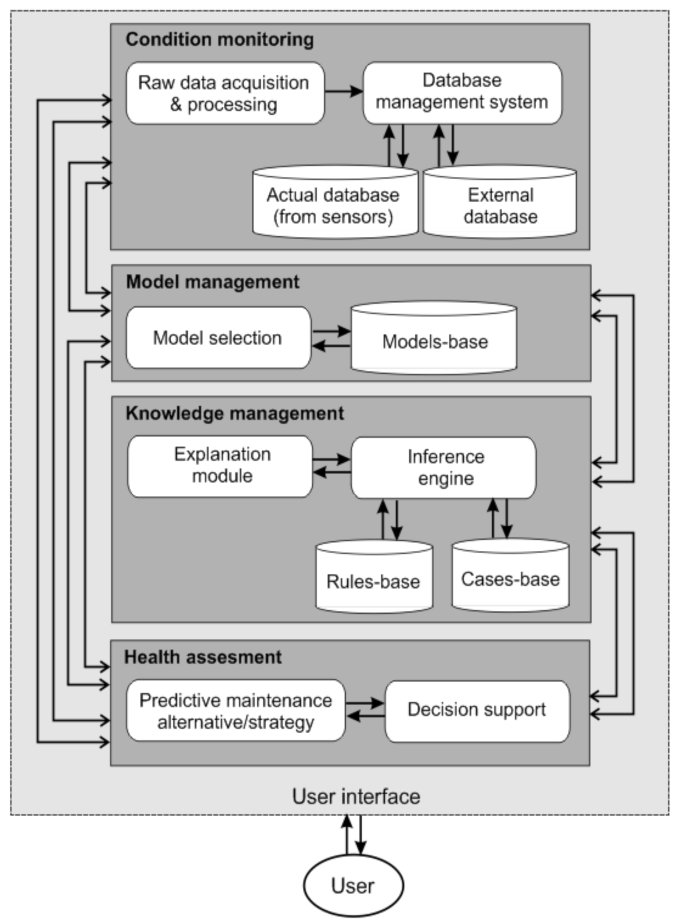

Fig. 4. An architecture for engineering e-maintenance platform

The first layer represents the condition monitoring module which collects and process data acquiring and information fusion combined with signal processing. The signal processing of sensor data is one of the most important functions of structural health monitoring systems for goal of predictive maintenance. The input raw data is adjusted, (the data is removed to get rid of noises and is normalized if required), in the pre-conditioning of data stage. Immediately after, useful information is extracted. The condition 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 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 condition monitoring layer should also be able to generate alerts based on preset operational limits or changes in the trend. The collected data are assessable through database management system as aid in the decision making process.

The second layer consists of module for model management. 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 models 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.

A knowledge management subsystem is proposed as a third layer in intelligent e-maintenance system. The engineering condition based maintenance is a specific 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 used for structure health management to recommend courses of action and decisions. This layer is composed of knowledge management system, knowledge base (rules- and cases-bases), 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 or cases. 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 is 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 (cases) needed for case- based reasoning. Case-based reasoning solves new problems by retrieving relevant prior cases and comparing and adapting them to fit new situations. Case-based 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. Case-based 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 case-based 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 case-based reasoning make it appropriate for diagnosis, prognosis, and predictive maintenance. The inference engine applies the knowledge base to the particular fact 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 decisions about the 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.

Health assessment layer is intended to receive data from different condition monitoring sources. The primary focus of the health assessment is to prescribe if the health of the monitored component, sub-system or system has degraded. Health assessment decision making relies heavily on the availability of relevant information in the right format and at the right time. On this layer data from all the prior layers are taken into account. The primary focus is to calculate the future health of equipment (machine), with account taken to the future usage prognostics or the so called remaining useful life.

Forecasting deterioration of the engineering systems characteristics during the time and proper decisions making is associated with considerable uncertainty. Decision maker in uncertainty conditions has idea about the goals to be achieved, but information about alternatives and future events is incomplete. Usually, there is no sufficient data to assess the risk of each alternative.

In cases like these, the decision maker preferences can be considered as a function called preference utility (optimization) function $f(x)$, on the set of possible alternatives $x = \{x_1, x_2, \ldots, x_m\}$ under environment states $s = \{s_1, s_2, \ldots, s_n\}$.

The decision maker can assess the usefulness of alternatives x_i, $i = 1, 2, \ldots, m$ by using an optimization approach as:

$$x_{opt} = max\ f(x) \tag{1}$$

s.t.

$$x = \{x_1, x_2, \ldots, x_m\} \quad (2)$$

$$s = \{s_1, s_2, \ldots, s_n\} \quad (3)$$

The following optimization criteria are used accordingly the decision maker point of view in the health assessment layer in Fig. 4.

- **Wald Criterion:** In this case, the decision maker selects the strategy associated with the best possible worst outcome regardless of whether probabilities are available or not. For each alternative solution x_i $(i = 1, 2, \ldots, m)$ the worst output $min\ E_{ij}\ (j = 1, \ldots, n)$ is defining. Next, an alternative solution is determined for which is the $min\ E_{ij}\ (j=1,\ldots,n)$ has maximum magnitude [20], [21]:

$$x_{opt} => max\ min\ E_{ij}\ (i=1,2,\ldots,m),\ (j=1,2,\ldots,n) \quad (4)$$

- **Savage's Minimax Regret:** The Savage minimax regret criterion is looking at a small loss of efficiency due to missed opportunities and is calculated by the relation:

$$R_{ij} = |E_{ij} - max\ E_{ij}| \quad (5)$$

Based on a "regret matrix" which compares (subtracts) the highest outcomes of each strategy from other outcomes [22]. The Wald' solution rule (maximin/minimax) is applied to this new matrix to gain the minimax regret solution. Optimum would be the minimum losses value R_{ij} among all alternatives:

$$x_{opt} => min\ max\ R_{ij}\ (i=1,2,\ldots,m),\ (j=1,2,\ldots,n) \quad (6)$$

- **Laplace Criterion:** The core of Laplace principle is based on the fact that if there is no information to determine a condition as more likely than another, then the optimal solution is determined as:

$$x_{opt} \Rightarrow max_i\left(\sum_{j=1}^{n}\frac{E_{ij}}{n}\right) \quad (7)$$

Here, all possible states have equal probability when no other information is available [23].

- **Hurwicz Criterion:** This decision criterion is a simplified version of Laplace principle and involves the identification of the worst and best outcomes for each strategy. Under certain probabilities of particular states, the arithmetic average of the results of the best solutions is taken [23]. The optimal solution is determined taking into account both a minimum and maximum profit:

$$x_{opt} => max\ \{\alpha\ max\ E_{ij} + (1-\alpha) min\ E_{ij}\} \quad (8)$$

where α is optimism coefficient ($0 < \alpha < 1$). When $\alpha = 0$, the Hurwicz solution is the same as the pure Wald solution; when $\alpha = 0.5$ corresponds to the equivalent antagonistic and friendly environment and in case of $\alpha = 1$ corresponds to the maximum favorable environment.

VI. Numerical Illustration of Different Strategies Selection

To illustrate numerically the advantage of the proposed intelligent concept for decision making, an easy to understand example is described. A manufacturing company is equipped with various machines, which have different reliability requirements, safety levels, failure effect, and impact on the company's gains. Let us consider three maintenance alternatives (to repair, to replace, to do nothing) for each of machines. The maintenance decision depends on the machines' health assessment (high, average, low). The alternatives benefits evaluations E_{ij} are shown in Table I.

TABLE I. Alternatives Benefits Evaluations

Alternatives	**Benefits Evaluations**		
	P1	***P2***	***P3***
A1	60	30	65
A2	40	20	70
A3	80	10	-5

Using of Wald criterion (pessimistic) the minimum value on each table row is chosen and then the maximum of them is selected, i.e. the decision is:

$$x_{opt} = \max(30;20;-5) = 30$$

The Savage's minimax regrets are calculated as:

$$r_{i1} = \max(60;40;80) - E_{i1}$$

$$r_{i2} = \max(30;20;10) - E_{i2}$$

$$r_{i3} = \max(65;70;-5) - E_{i3}$$

The calculations results are shown in Table II.

TABLE II. Savage's Minimax Regrets

Regrets			**Mini-max**
20	0	5	20
40	10	0	40
0	20	75	75

$$x_{opt} = \min(20; 40; 75) = 20$$

This criterion indicates that alternative A1 has the lowest regret and is the best choice.

Applying of Laplace criterion results in calculation of:

$$x_{opt} = \max\{(\frac{1}{3}(60+30+65)),(\frac{1}{3}(40+20+70)),$$
$$(\frac{1}{3}(80+10-5))\} = \max(51.6; 43.3; 28.3) = 51.6$$

The decision is to choose alternative A1 with expected benefit of 51.6.

According to the Hurwicz criterion an optimism coefficient value of 0.25 is set. It is used to calculate the following values:

$$x_{opt} = \max\{(0.2*65+0.8*30),(0.2*70+0.8*20), (0.2*80+0.8*(-5))\} = \max(37;30;12) = 37$$

Again the decision is to choose alternative A1 with expected benefit of 37.

Combining the information of all layers with optimization approaches would assist the decision maker in his/her decision making for engineering systems maintenance under uncertainty or incomplete information conditions.

VII. CONCLUSION

In the current paper a concept of intelligent e-maintenance decision making system for engineering condition based maintenance is proposed. The described concept is built on four abstraction levels, to serve as reference for developing of intelligent e-maintenance decision support system. It extends the concept of decision support system with the expert system advantages. The advances of expert system embrace symbolic reasoning and explanation capabilities. This is an efficient addition in making of strategic decisions by intelligent interpretations of various alternatives. The essence of the proposed concept of intelligent e-maintenance decision making system is the ability to integrate actual information from structure health monitoring and structure health modeling modules with knowledge management. The condition based 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. Health assessment layer allows DM to assess the usefulness of different alternatives by using optimization approaches to forecast deterioration of the system during the time.

The benefits of the proposed concept of intelligent e-maintenance decision making system for engineering condition based maintenance is in intelligent decision support leading to efficiency savings, only carrying out maintenance when necessary but in-time to prevent failures. This would lead to substantial increases in productivity and decreasing of the maintenance costs. The proposed concept of intelligent e-maintenance decision making system for engineering condition based maintenance is intended for application for metallurgical company equipment predictive maintenance.

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