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Abstract

Purpose – The purpose of this paper is to perform an extensive literature review in the area of decision making for condition-based maintenance (CBM) and identify possibilities for proactive online recommendations by considering real-time sensor data. Based on these, the paper aims at proposing a framework for proactive decision making in the context of CBM.
Design/methodology/approach – Starting with the manufacturing challenges and the main principles of maintenance, the paper reviews the main frameworks and concepts regarding CBM that have been proposed in the literature. Moreover, the terms of e-maintenance, proactivity and decision making are analysed and their potential relevance to CBM is identified. Then, an extensive literature review of methods and techniques for the various steps of CBM is provided, especially for prognosis and decision support. Based on these, limitations and gaps are identified and a framework for proactive decision making in the context of CBM is proposed.
Findings – In the proposed framework for proactive decision making, the CBM concept is enriched in the sense that it is structured into two components: the information space and the decision space. Moreover, it is extended in a way that decision space is further analyzed according to the types of recommendations that can be provided. Moreover, possible inputs and outputs of each step are identified.
Practical implications – The paper provides a framework for CBM representing the steps that need to be followed for proactive recommendations as well as the types of recommendations that can be given. The framework can be used by maintenance management of a company in order to conduct CBM by utilizing real-time sensor data depending on the type of decision required.
Originality/value – The results of the work presented in this paper form the basis for the development and implementation of proactive Decision Support System (DSS) in the context of maintenance.

Keywords Decision making, Condition-based maintenance, E-maintenance, Proactivity, Real-time data, Recommendations
Paper type Research paper

1. Introduction

In manufacturing, equipment maintenance is a significant contributor to the total company's cost, so having an optimal maintenance policy in terms of cost, equipment downtime and quality is an important efficiency enabler (Waeyenbergh and Pintelon,

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2004; Garg and Deshmukh, 2006). Maintenance is related to all the processes of a manufacturing firm and focusses not only on avoiding the equipment breakdown but also on improving business performance, for example, in terms of productivity, elimination of malfunctions, etc. Various maintenance policies have been examined in both the academic and industrial realms and a multitude of maintenance strategies have been recommended in an effort to develop a holistic approach for maintenance management, which supports both reactive and proactive support maintenance actions (Waeyenbergh and Pintelon, 2004).

"Proactivity" in the context of information systems refers to the ability to avoid or eliminate undesired future events or exploit future opportunities by implementing prediction and automated decision making technologies (Engel and Etzion, 2011). Proactivity is leveraged with novel information technologies that enable decision making and support human actions before a predicted critical event occurs. Application domains that can take advantage of such technologies include transport, fraud management and maintenance (Artikis *et al.*, 2014; Magoutas *et al.*, 2014). In manufacturing, sensors have the capability of measuring a multitude of parameters frequently and collecting plenty of data. Analysis of Big Data, both historical and real-time, can facilitate predictions on the basis of which proactive maintenance decision making can be performed.

E-maintenance is related to the notion of proactivity because it supports the transmission of the enterprise from "fail and fix" to "predict and prevent" concept while, at the same time, maintenance is addressed as an enterprise process, integrated with both internal and external business processes (Macchi *et al.*, 2014), for improving business performance (Lee *et al.*, 2006; Iung *et al.*, 2009). E-maintenance assumes that data should be available to all enterprise components and actors with the aid of ICT at the right time and place in order to make optimal maintenance decisions based on underlying predictions (Iung *et al.*, 2009).

Generally, the need for a business turning from reactive to proactive is increasing. Proactive enterprise leads to increased situation awareness capabilities even ahead of time. This will lead to a new class of enterprise systems, proactive and resilient enterprises, that will be continuously aware of that what "might happen" in the relevant business context and optimize their behavior to achieve what "should be the best action" even during stress and balancing on demanding margins. Proactive enterprise systems will be able to suggest early on to the decision makers the most appropriate process adjustments to avoid singular system behavior and optimize its performance (Magoutas *et al.*, 2014).

Although during the last years there have been some efforts toward increasing the level of proactivity in maintenance decision making, existing approaches are still under development and suffer from some limitations. The degree of proactivity is usually low and decisions are narrowed to recommendations about the maintenance schedule, i.e., the sequence of maintenance actions, the maintenance strategy or, more rarely, the optimal time of applying a predefined action. In other words, optimization is done for one criterion at a time, while recommendations involve a general decision. Moreover, contributions are not presented as part of a wider framework that can support their integration in manufacturing processes. In addition, the vast majority of prognostic models are validated within a laboratory environment by doing experiments and not in industrial settings. This paper aims to review existing works in maintenance decision making methods and synthesize a generic framework that can support the development of proactive decision support systems (DSS) that include predictions and proactive actions based on these predictions (Engel *et al.*, 2012). To the best of our knowledge, there is no a holistic e-maintenance framework for decision making in CBM providing reactive and, even more importantly, proactive support based on the degradation state of equipment and the prediction of its evolution, exploiting large amounts of condition data collected automatically by sensors. In this paper we aim to fill this gap by providing a Proactive Decision Making Framework for Condition-Based Maintenance (CBM).

The paper is structured in five sections. Section 2 describes the theoretical background and the motivation for creating a framework for proactive decision making in the context of CBM. Section 3 provides a review of methods and techniques used in the steps of CBM, focussing on prognosis and decision support, while Section 4 presents the framework for maintenance decision making. Section 5 presents a practical demonstration of the proposed framework. Finally, Section 6 discusses the added value and practical implications of the proposed framework, while Section 7 concludes the paper and presents our plans for future work.

2. Decision making for maintenance operations

2.1 Types of maintenance

Although there is no absolute agreement in the literature about the classification of maintenance types, we can broadly distinguish between three categories: breakdown maintenance which takes places when a failure occurs; time-based preventive maintenance which sets certain activities when a defined period of time passes; and CBM which recommends actions according to the current and future health state of the manufacturing system based upon data gathered through condition monitoring (Jardine *et al.*, 2006).

Breakdown maintenance is the oldest type of maintenance that fixes equipment as soon as they need to. Time-based preventive maintenance is the evolution of breakdown maintenance (Jardine *et al.*, 2006). Time-based preventive maintenance is widely used in industry; however, companies are increasingly turning to CBM, with manufacturing companies considering the use of condition monitoring. Currently, even large manufacturing companies either do not use sensors for measuring indicators of equipment degradation at all or, even if they do so, they have not developed a complete CBM strategy in order to utilize its benefits. However, CBM is becoming essential for every manufacturing business as products have become more and more complex thanks to the evolution of technology and thus, quality and reliability have become issues of high significance (Jardine *et al.*, 2006; Peng *et al.*, 2010). Consequently, the costs of time-based preventive maintenance have increased and CBM has started to be evolved as a novel lever for maintenance management (Jardine *et al.*, 2006). CBM is tightly linked to the notion of proactivity which is the focus of our study and hence we examine it in detail below.

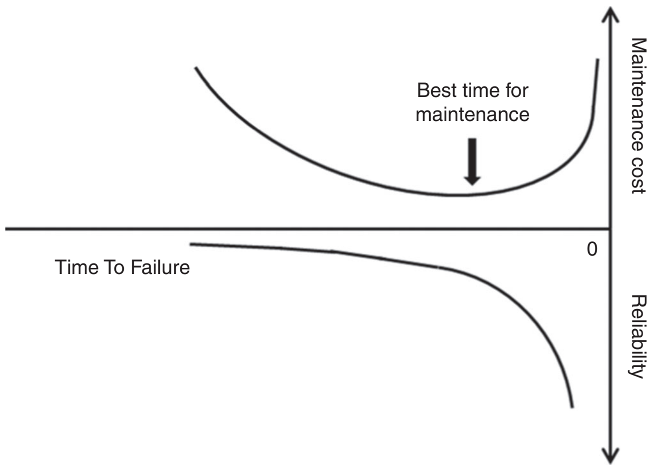
2.2 CBM

CBM relies on diagnostic and prognostic models and uses them to support decisions about the appropriate maintenance actions based on the current health state of a system and/or its predicted performance and remaining lifetime. CBM can be applied for supporting decisions either about Corrective And Preventive Actions (CAPA) or about proactive actions. In the first case, only diagnosis is required so that the actual condition of the system is identified and if it has been failed, decisions for repair CAPA are taken. In the second case, prognosis is required as well, so that future condition of the system is predicted and decisions about proactive maintenance actions are taken (Jardine *et al.*, 2006; Peng *et al.*, 2010; Voisin *et al.*, 2010).

Several maintenance frameworks have been proposed in the literature outlining the steps involved in performing CBM. Lee *et al.* (2004) describes three core steps: first, data acquisition, to collect the data; second, data processing, to handle the data; and third, maintenance decision making, to decide about the optimal maintenance policy. Peng *et al.* (2010) focussed on the third step (maintenance decision making), further detailing it into diagnosis and prognosis. The authors also indicated the need for historical data and for the development of a model for representing system behavior. Irigaray *et al.* (2009) focussed on supporting CBM by storing relevant data and information and utilizing them so that the most appropriate decisions are drawn and are updated dynamically by means of a platform based on web services and a systematic process consisting of four layers: condition monitoring, assessment of the health state, prognosis and decision making.

Peng *et al.* (2010) described in detail a maintenance decision support framework consisting of five main steps: first, feature selection, which is conducted with the aid of historical data as well as several methods such as principal component analysis, genetic algorithms and support vector machine (SVM); second, data training (analysis); third, diagnostics and prognostics, by using real-time data; fourth, reliability and remaining useful life (RUL) where the result is verified and its precision is assessed in order to give feedback to steps second and fifth; and fifth, maintenance schedule, which considers the cost function which is extracted from the relationship between the maintenance cost, RUL and reliability of the system. Figure 1 depicts this relationship and shows that while time to failure is approaching zero, reliability is decreasing (Peng *et al.*, 2010). When time to failure becomes zero, a breakdown of the equipment occurs. The best time to do maintenance is when the maintenance cost is minimum and reliability has started to increase significantly.

An important principle of CBM is the P-F curve, which can be used to estimate RUL of some part of equipment. Figure 2 illustrates how a failure starts and deteriorates to the point at which it can be detected (the potential failure point "P"). Thereafter, if it is not



Source: Based on Peng *et al.* (2010)

Figure 1.
Relationship among RUL, reliability and maintenance cost

detected and no suitable action is taken, it continues to deteriorate – usually at an accelerating rate – until it reaches the point of functional failure (Point "F"). The amount of time which elapses between the point where a potential failure occurs and the point where it deteriorates into a functional failure is known as the P-F interval (Veldman *et al.*, 2011). This interval can be seen as an opportunity window during which actions can be taken with the aim to eliminate the anticipated functional failure or mitigate its effect.

Arguably the most generic conceptual framework for proactive maintenance decision support has been proposed by Voisin *et al.* (2010). This framework considers the interactions of prognosis with the whole business environment and represents the business processes which are integrated with prognosis as shown in Figure 3 (Iung *et al.*, 2009; Voisin *et al.*, 2010). Moreover, it separates the decision support step

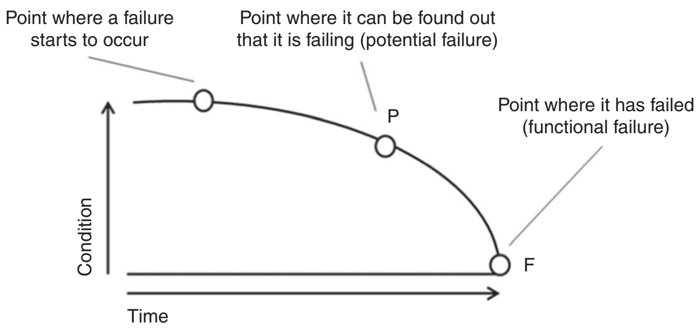
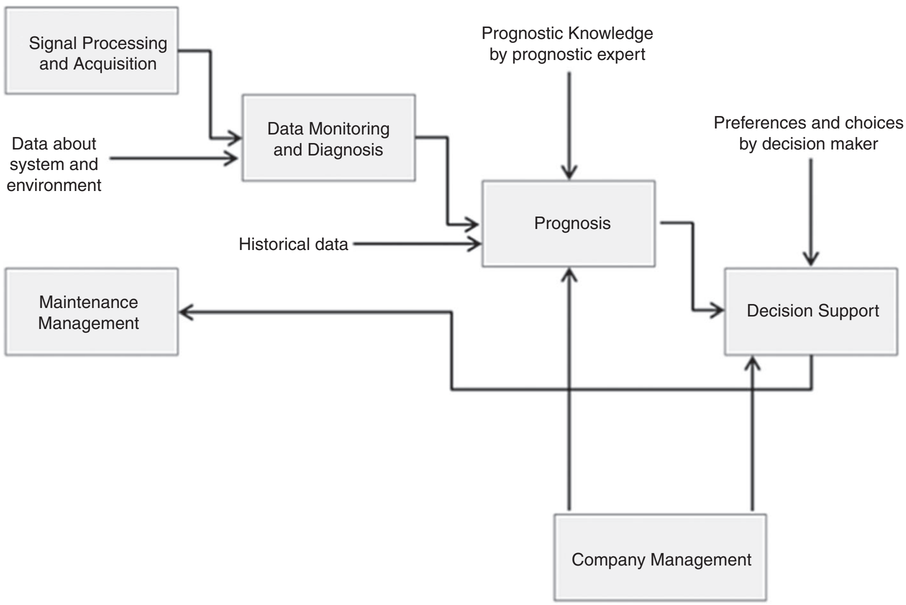


Figure 2.
P-F curve



Source: Adapted from Voisin *et al*. (2010)

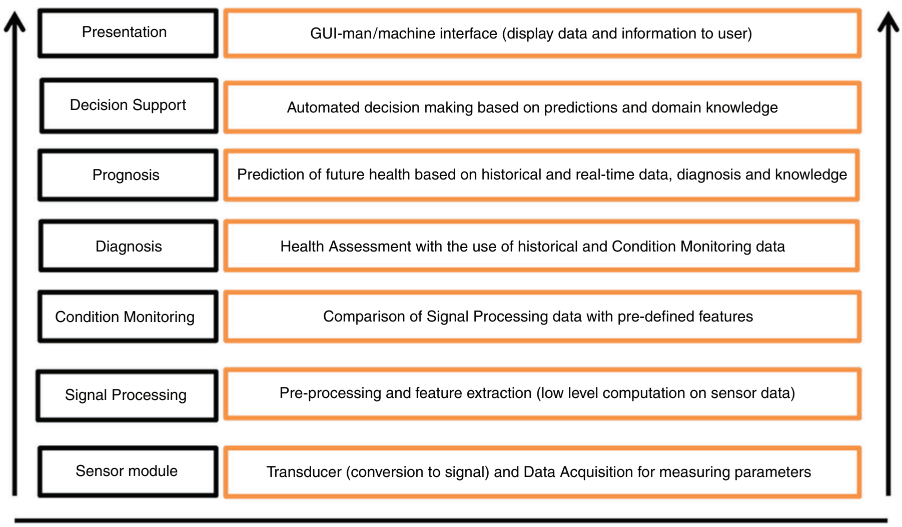
Figure 3.
The role of diagnosis
and prognosis
in CBM

from diagnostics and prognostics by combining and updating two earlier frameworks (Léger and Morel, 2001; Muller *et al.*, 2008a; Lebold and Thurston, 2001).

In the industrial realm, the open systems architecture for CBM (OSA-CBM) framework has already been implemented in several industries, such as aerospace industry within the framework of Integrated Vehicle Health Management (IVHM) (Lebold and Thurston, 2001; Dunsdon and Harrington, 2008; Benedettini *et al.*, 2009). The OSA-CBM framework consists of seven sequential layers as shown in Figure 4. Its goal is to enable the integration of prognostics and equipment health management information from a variety of sources. OSA-CBM describes the entire process of CBM starting from the collection of data and ending with the decision making step and the presentation of the results (Lebold and Thurston, 2001; Dunsdon and Harrington, 2008).

2.3 E-maintenance

E-maintenance refers to the convergence of emerging information and communication technologies with DSS which take into account the resources, services and management to enable decision making in a proactive way (Muller et al, 2008a). E-maintenance has become important in the last years due to the emergence of technologies which are able to optimize maintenance-related workflows and the integration of business performance, which enable openness and interoperation of e-maintenance with other components of e-enterprise (Iung *et al.*, 2009). This support does not include only technologies, but also operations and processes related to maintenance such as condition monitoring, diagnostics, prognostics, etc. (Muller *et al.*, 2008a; Muller *et al.*, 2008b; Irigaray *et al.*, 2009; Levrat and Iung, 2007). E-maintenance is considered not only in production and operation stages but also as an integral part of the whole lifecycle management. Therefore, apart from production issues, e-maintenance should also embed eco-efficiency and product design, disassembly and recycling in a way that consists a useful tool for business process improvement in the context of maintenance lifecycle management (Takata *et al.*, 2004; Iung *et al.*, 2009).



Source: Lebold and Thurston (2001)

Figure 4.
The OSA-CBM framework

Next generation DSS for maintenance can use raw sensors events, domain knowledge events, effect events, cause events and action events (Dunkel *et al.*, 2011). Future DSS should also include predictions and proactive actions based on these predictions (Engel *et al.*, 2012). Currently however, existing DSS in manufacturing support only reactive event-driven applications as actions are taken after events have occurred.

A conceptual architecture for proactivity comprising predictive and proactive agents for forecasting and automated decision making technologies, respectively, has been proposed by Engel and Etzion (2011). Moreover, Artikis *et al.* (2014) presented a conceptual methodology for scalable processing and event-driven decision making which uses real-time optimization techniques in order to develop real-time proactive planning tools applicable to traffic and credit card fraud management with various levels of autonomy. However, there are opportunities for the development and implementation of a holistic framework for providing novel information systems in alignment with the e-maintenance needs of modern enterprises leveraging the potential applications of proactivity and facilitating the way decisions are made.

3. Review of CBM methods and techniques

There are three main steps in CBM: diagnosis, prognosis and decision support (Voisin *et al.*, 2010; Peng *et al.*, 2010). Diagnosis has to do with the actual monitoring of a system and detection of failures, while prognosis has to do with prediction of the RUL of the system based upon its actual health state (Venkatasubramanian, 2005). Although diagnosis, which is usually mentioned as the step before prognosis, is not always prerequisite, it can efficiently complement the proactive maintenance DSS in cases when an undesired effect which has not been predicted occurs (Jardine *et al.*, 2006; Peng *et al.*, 2010).

Methods used for CBM can be classified in four categories (Venkatasubramanian, 2005; Goh *et al.*, 2006): model-based; knowledge-based; data-driven; and combination of them. In the current research work, data-driven methods are examined. However, they are usually accompanied with some degree of knowledge depending on the availability of data and the required output.

There are research works using methods for providing a diagnostic output, a prognostic one or decision support, in other words they may stop to a different step of CBM, based on Figure 3. For example, research works dealing with prognosis cover the three first CBM steps of Figure 3, while those dealing with decision support cover the decision support step as well. In other words, in the latter case, prognostic methods provide a prediction based on which recommendations are generated.

Diagnosis and reactive recommendations (CAPA) is a well explored area (Ding *et al.*, 2002; Nandi *et al.*, 2005; Jung *et al.*, 2006; Qian *et al.*, 2008; Bennouna and Roux, 2013; Ruiz-Mezcua *et al.*, 2011; Prakash and Ceglarek, 2013; Pal and Ceglarek, 2013; Pal *et al.*, 2014). For this reason, the focus of the current review is prognosis and prognostic-based decision making.

The papers examined were identified by searching Google scholar with the keywords "CBM," "Condition Based Maintenance," "recommendations," "decision support," "decision making,"' manufacturing," "maintenance," "e-maintenance," "real-time" and "proactivity" in various combinations among them. We focussed on papers dealing with the decision step of CBM. However, we realized that most of them either were narrowed in the prognostic step of CBM (without reaching the decision step for the provision of recommendations) or proposed a combination of methods so that they develop a prognostic model based on real-time data and then, based on this, they provide recommendations for maintenance. The focus was on most recent papers, after 2008, with exceptions in cases where an older paper satisfied the keywords and proposed a novel and useful method which has not been extended until now.

3.1 Prognosis

Voisin *et al.* (2010) focussed on the components of the prognostic process by focussing on the prognosis sub-steps and illustrating its interactions with the other components of the CBM strategy's steps, as shown in Figure 5.

A significant body of research regarding the development of prognostic models has been conducted. Several methods and techniques have been used in order to estimate the RUL/ remaining life distribution (RLD) and/or the probability distribution about the occurrence of a breakdown or other undesired events.

Banjevic and Jardine (2006) presented the failure process as a discrete Markov process and Kolmogorov equation is used accompanied with product-integration method for the calculation of RUL. Muller *et al.* (2008a) proposed a methodology which implements the proactive logic in a prognosis model by combining probabilistic (dynamic Bayesian networks – DBN) and event methods for degradation modeling and monitoring.

Salfner and Malek (2007) used HSMM in order to conduct online failure prediction by using event-driven sources such as errors. The methodology was compared with Dispersion Frame Technique, a reliability model and an event-based method in terms of several performance measures such as precision, recall, F-measure, false-positive rate and computing time. Gebraeel and Lawley (2008) developed a degradation model based on condition monitoring with the use of NN. The model estimates and continuously updates the RLD.

Gebraeel *et al.* (2009) presented a degradation modelling framework without having historical data about degradation. So, they assume that failure time data follow a Bernstein distribution to estimate the characteristics of the stochastic parameters needed for the degradation modelling. Moreover, they assume that degradation follows either a linear or an exponential distribution. The proposed methodology estimates and continuously updates the RLD. Caesarendra *et al.* (2011) developed a prognostic model based on statistical analysis to identify the actual degradation of the component and to estimate the failure probability and its variance.

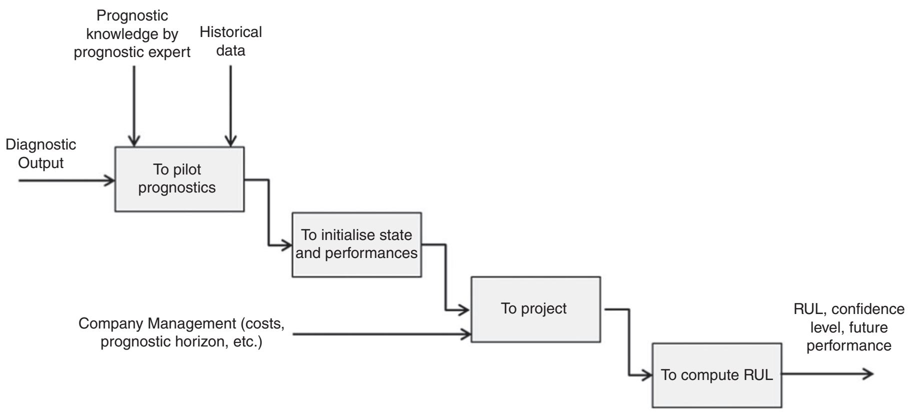


Figure 5.
Components of prognostic process

Source: Based on Voisin *et al*. (2010)

Kim *et al.* (2012) presented a prognostic methodology for bearings of high pressure-liquefied natural gas pumps which models the dynamic and stochastic degradation process and estimates the RUL with the use of SVM. Tobon-Mejia *et al.* (2012a) proposed a methodology for real-time data-driven prognosis with the use of a Mixture of Gaussians- Hidden Markov Models (MoG-HMMs) and DBN, accompanied with other techniques such as Baum-Welch algorithm, Viterbi algorithm, data clustering and curve fitting, in order to calculate the RUL of the degrading machine tool and the relevant confidence level.

Tobon-Mejia *et al.* (2012b) proposed a prognostic methodology for the estimation of RUL and the relevant confidence level by using Wavelet Packet Decomposition technique and the MoG-HMM as well as Baum-Welch algorithm and Viterbi algorithm. Ferreiro *et al.* (2012) presented a framework for prognosis based on BNs embedded to the IVHM concept. The output of the prognostic model is an estimation of RUL of the component of the aircraft as well as its confidence values. The authors argue that this prognostic information can contribute to the reduction of the costs caused by cancellations or delays due to failures.

Bangalore and Tjernberg (2013) proposed a prognostic model based on ANN which are updated continuously with the aid of an automated self-evolving approach and the training data set is optimized. The model utilizes data taken from a Supervisory Control and Data Acquisition (SCADA) system which is used for monitoring parts of equipment.

Table I shows the prognostic methods that each paper uses accompanied with their inputs and outputs.

Although a variety of methods have been used in order to provide useful diagnostic and prognostic capabilities by utilizing real-time data from the manufacturing domain such as the ones examined here, most have a low level of autonomy because they narrow their decision support for human operators and do not support partial or full autonomous decision making (Peng *et al.*, 2010; Voisin *et al.*, 2010; Artikis *et al.*, 2014).

3.2 Decision support

Several research works have examined and developed autonomous decision making methods based on both historical and real-time data as well as expert knowledge with the aim to address different maintenance challenges for components subjected to condition monitoring.

Maintenance decision support is related to reliability, safety and environmental issues as well as costs because of downtime of the equipment in case of a breakdown or malfunctions of machines so it is a crucial operation function of the enterprise (Peng *et al.*, 2010). First, diagnostic and/or prognostic methods are applied and then, the system recommends appropriate actions either for immediate implementation due to an actual failure (reactive) or for future implementation in order to avoid an undesired event (proactive actions). However, the latter is the least explored area.

Several research works dealing with maintenance decision support are based on predictions. Predictions are not considered as given in these works, e.g., as prognostic functions, probabilistic estimates or expert knowledge. Hence, research works dealing with decision support usually develop a prognostic model analyzing and processing the historical and real-time data available and, based on these, they develop decision methods in order to provide prognostic-based recommendations.

Table I.
Reviewed research works on prognosis

References	Input	Prognostic methods	Output
Muller *et al.* (2008a)	Real-time data: degradation Historical data: historical failure/degradation data Knowledge: process knowledge	Dynamic Bayesian networks (probabilistic model) Event model	Probability distribution over all variables Consistency of prognosis
Banjevic and Jardine (2006)	Real-time data: degradation (e.g. vibration or oil) Historical data: historical failure/degradation data Knowledge: wear stages	Degradation Modelling Markov Chain	Reliability functions Calculation of RUL as a function of the current conditions
Salfner and Malek (2007)	Real-time data: real time monitoring of error logs Historical data: recorded error logs	Hidden Semi-Markov Models (HSMMs) (that use event-driven sources such as errors)	Forecasting of the occurrence of failures
Gebraeel and Lawley (2008)	Real-time data: degradation signals (e.g. vibration signals) Historical data: historical degradation data (e.g. vibration)	Neural Network Degradation Modelling	Computing residual life distribution Updating residual life distribution
Gebraeel *et al.* (2009)	Real-time data: degradation signals (e.g. vibration signals) Historical data: historical failure time data Knowledge: wear stages	Degradation modelling Bayesian networks	Residual life prediction
Caesarendra *et al.* (2011)	Real-time data: vibration condition monitoring data Historical data: bearing failure data	Relevance vector machine Logistic regression Autoregressive moving average Dempster-Shafer regression Statistical process control	Prediction of the failure probability of individual units of bearing samples Analysis of variance of the failure probability
Kim *et al.* (2012)	Real-time data: vibration signals Historical data: historical degradation (vibration) data Knowledge: wear stages	Support vector machine (SVM) classifier	Optimal prediction of RUL

(*continued*)

References	Input	Prognostic methods	Output
Tobon-Mejia *et al.* (2012a)	Real-time data: degradation data Historical data: degradation data Knowledge: wear stages	Mixture of Gaussian-Hidden Markov model Dynamic Bayesian network Baum-Welch algorithm Viterbi algorithm	RUL and confidence value
Tobon-Mejia *et al.* (2012b)	Real-time data: degradation signals (e.g. vibration signals) Historical data: historical degradation data (e.g. vibration) Knowledge: wear stages	Mixture of Gaussian-Hidden Markov model Dynamic Bayesian network Wavelet packet decomposition Baum-Welch algorithm Viterbi algorithm	RUL and confidence value
Ferreiro *et al.* (2012)	Real-time data: degradation signals Historical data: historical degradation data Knowledge: domain knowledge about causes and effects	Bayesian networks	Time to failure RUL and confidence value
Bangalore and Tjernberg (2013)	Real-time data: signals from SCADA system Knowledge/historical data: normal behaviour of components	Artificial neural network	Fault prognosis

Table I.

Kaiser and Gebraeel (2009) proposed a method for predictive maintenance management by utilizing real-time degradation data. They developed a degradation model in order to estimate and update in real time the RLD of some part of equipment and the most suitable maintenance policy is recommended based on the frequency of failures and the maintenance costs.

Besnard and Bertling (2010) presented a method for applying CBM to wind turbine blades. Provided that degradation of a part of equipment can be classified into one category in terms of severity of damage, the method optimizes decisions about different maintenance strategies. The strategies examined in this paper are visual inspection, inspection with a condition-monitoring technique and online condition monitoring.

Besnard *et al.* (2011) presented a model for the optimization of maintenance planning in offshore wind farms. The model uses stochastic optimization in order to perform the optimum maintenance schedule at the lowest cost based upon the wind and production forecasting.

Castro *et al.* (2012) proposed a cost modelling approach for predictive maintenance policy based on the RUL estimated after each inspection. The method recommends the optimal time of applying maintenance to avoid a future breakdown. The failures that are assumed to happen can depend on degradation or on immediate shocks of the equipment.

Wu *et al.* (2007) developed a DSS in order to minimize the expected cost by taking into account the RUL. The authors propose an ANN to predict and update in real-time the RUL of the equipment and cost modelling techniques accompanied with probability theory for calculating the replacement time which minimizes cost at each unit operational time.

Ivy and Nembhard (2005) proposed a method for recommending the optimal maintenance policy by using statistical quality control (SQC) and partially observable Markov decision process (POMDP). SQC techniques were used in order to define the observations distributions and the structure of POMDP. Results of POMDP were evaluated in terms of robustness and accuracy.

Aissani *et al.* (2009) used reinforcement learning and Markov decision process (MDP) in order to automate maintenance tasks scheduling in petroleum industry and to update them in real time. The model developed has multiple agents which function in the logic of continuous improvement by learning the best behaviours of their roles and improving the solution about the corrective and predictive tasks provided.

Elwany and Gebraeel (2008) proposed a decision model for component replacement and spare parts inventory based upon the RLD instead of failure time distribution. RLD is calculated and is continuously updated and is then used as input to the decision model which calculates the optimal replacement time as well as the optimal inventory ordering time.

Bouvard *et al.* (2011) proposed a method for the optimization of maintenance planning for systems with multiple components such as commercial heavy vehicles. First, maintenance actions are grouped according to the component to which they are linked. Then, degradation models are developed in order to monitor each component, recommend the optimal maintenance planning and update it dynamically when necessary.

Huynh *et al.* (2012) proposed a method for assessing, comparing and selecting the most appropriate and cost-effective maintenance policy for a single-unit degrading system under condition monitoring. Muller *et al.* (2007) proposed a methodology which implements the proactive logic in a prognosis model for supporting the maintenance strategy. This evolution of prognostic models combines probabilistic and event methods in order to evaluate different maintenance plans in terms of effectiveness and cost and to calculate the optimal maintenance policy.

Engel *et al.* (2012) provided a methodology for proactive event-driven computing with potential application to CBM, however, it is conceptually described and sets the guidelines for future development. Suitable methods for proactive applications could be BN and MDP.

Table II summarizes the prognostic-based decision support methods reviewed, as well as their inputs and outputs. The methods have been separated in two groups; one group supports the prognostic and the second the decision step. The prognostic step of CBM is the one that contributes to the input of the decision support step.

Despite the advances in CBM, limitations and open issues still exist, such as (Jardine *et al.*, 2006; Iung *et al.*, 2009; Peng *et al.*, 2010):

- Prognostic models used for CBM are not always continuously updated by real-time data through sensors, but they receive batches of data. This fact affects negatively the responsiveness of the system to provide prognostic information and recommendations for maintenance. The reason for this is that high computation speed is required, so an appropriate system needs to be developed.
- Although there are several theoretical research works, there is a limited number of practical applications.
- Recommendations of maintenance actions and maintenance policy for CBM are not usually embedded in integrated maintenance platforms.
- Despite the plethora of existing works for both prognosis and diagnosis in maintenance, most of them do not examine automation of decisions by providing recommendations for maintenance actions.
- E-maintenance could be a significant contributor to the conversion of maintenance from reactive to proactive.
- Collecting all necessary data (both historical and real-time) in order to develop a method which provides reliable results is a major challenge.

4. Proactive decision making framework for CBM

In this section we present a conceptual framework for supporting CBM decisions within an e-maintenance/real-time data infrastructure. As shown in Figure 6, our framework represents the sequence of steps, which need to be followed in order to support decision making in e-maintenance. The framework is based on the OSA-CBM framework (Lebold and Thurston, 2001) and the prognostic process outlined by Voisin *et al.* (2010), as outlined in Section 2. The conceptual framework of Figure 6 extends the aforementioned works in two ways: first, the CBM constituents are identified and structured in two categories and second, the decision support constituent is further analyzed according to the types of decisions that can be provided. Specifically, the two categories are the information space and the decision space. The former consists of diagnosis and prognosis and provides information about the current and the future health state of the equipment, respectively, while the latter consists of maintenance actions, both reactive and proactive ones. An integrated view of the information and decision spaces is a prerequisite for providing timely and reliable recommendations because the input of the decision space relies on the predictions made within the information space.

Table II. Reviewed research works on prognostic-based decision support

References	Input	Prognostic methods	Output	Input	Decision methods	Output
Kaiser and Gebraeel (2009)	Real-time data Vibration Historical data Failure times Degradation Downtime	Continuous-time continuous-state stochastic model Degradation modelling	Estimation of RLD	RLD Knowledge Costs (planned replacements and total maintenance costs) Process knowledge	Cost modelling Rules	Compute/update/ evaluate maintenance schedule
Besnard and Bertling (2010)	Real-time data Degradation Knowledge Lifetime Failures States	Degradation modelling Markov chain Sensitivity analysis	RUL Failure rate-crack initiation rate Mean crack time to failure	RUL Failure rate Average production Maintenance and production costs	Continuous time Markov chain optimization Rules	Optimal maintenance strategy
Besnard *et al.* (2011)	–	–	–	Knowledge Wind forecasting Failure rate List of actions Repair time Maintenance and logistics costs	Stochastic optimization Rules	Cost for production losses and transportation that could be saved
Castro *et al.* (2012)	Real-time data Degradation Historical data Degradation Knowledge Threshold limit	Degradation modelling Statistical analysis	Mean residual life Probability of preventive and corrective replacement Replacement time	Mean residual life Probability of preventive and corrective replacement Expected downtime Replacement time Knowledge Costs of preventive and corrective replacement Cost of inspection	Optimization (considering both degradation and traumatic shocks)	Minimized long-run expected maintenance cost Optimum policy

(continued)

References	Input	Prognostic methods	Output	Input	Decision methods	Output
Wu *et al.* (2007)	Real-time data Vibration Historical data Vibration Knowledge Failure threshold	Artificial neural network Non-linear programming (Levenberg-Marquardt algorithm) Moving average	Residual life percentile prediction Marginal residual life distribution	Predicted residual life percentile Marginal residual life distribution Knowledge Operating time Corrective and predictive maintenance costs	Non-linear programming Cost matrix/ expected cost optimization	Predicted failure time Minimized cost Optimal replacement time
Ivy and Nembhard (2005)	Real-time data Degradation Knowledge States Probabilities Threshold	Statistical quality control (SQC)	Transition matrix Estimation of distribution parameters	Transition matrix Estimation of the distribution parameters Total expected cost Maintenance costs	Partially observable Markov decision process (POMDP)	Minimum total expected cost Maintenance actions
Aissani *et al.* (2009)	Real-time data Failures Historical data Failures Knowledge States Operational times Actions	Reinforcement learning (SARSA algorithm): solve selection and reward function	Solution of reward function Solution of selection function Probabilities of occurrence of events	Solution of reward function Solution of selection function Probabilities of occurrence of events	Markov decision process	Generate online scheduling solutions for predictive and corrective maintenance tasks on-line
Elwany and Gebraeel (2008)	Real-time data Vibration Historical data Vibration	Degradation modelling	RLD	RLD Knowledge Planned and failure replacement cost Holding and shortage costs Lead times	Optimization (replacement model)	Optimal replacement and inventory ordering times

(*continued*)

Table II.

Table II.

References	Input	Prognostic methods	Output	Input	Decision methods	Output
Bouvard *et al.* (2011)	Real-time data Degradation Knowledge Deterioration parameters	Degradation modelling Statistics	Failure probability function Degradation path Time-to-failure	Failure probability function Estimated degradation path Time-to-failure Knowledge Maintenance costs	Maintenance optimization	Optimal grouping structure Optimal maintenance dates and costs
Huynh *et al.* (2012)	Real-time data Periodic inspection Knowledge Degradation process Threshold	Degradation modelling Statistics particle filtering	Condition reliability Measurement of uncertainty Probability density function	Condition reliability Measurement of uncertainty Probability density function Knowledge Cost function	Optimization-dynamic replacement model Rules	Predictive replacement time estimation Optimized cost
Muller *et al.* (2007)	Real-time data Failures Historical data Failures Knowledge Process	Dynamic Bayesian networks Event model	Probability distribution over all variables Consistency of prognosis	Probability distribution over all variables Consistency of prognosis Knowledge List of actions Costs	DBN Utility function Multi-criteria analysis Markov chain	Assessment of maintenance alternatives Optimal maintenance policy
Engel *et al.* (2012)	Real-time data Failures Historical data Failures	Bayesian networks	Probability distribution of time to breakdown	Probability distribution Time to breakdown Knowledge States Actions Cost function	Markov decision process	Optimal action Optimal time of action

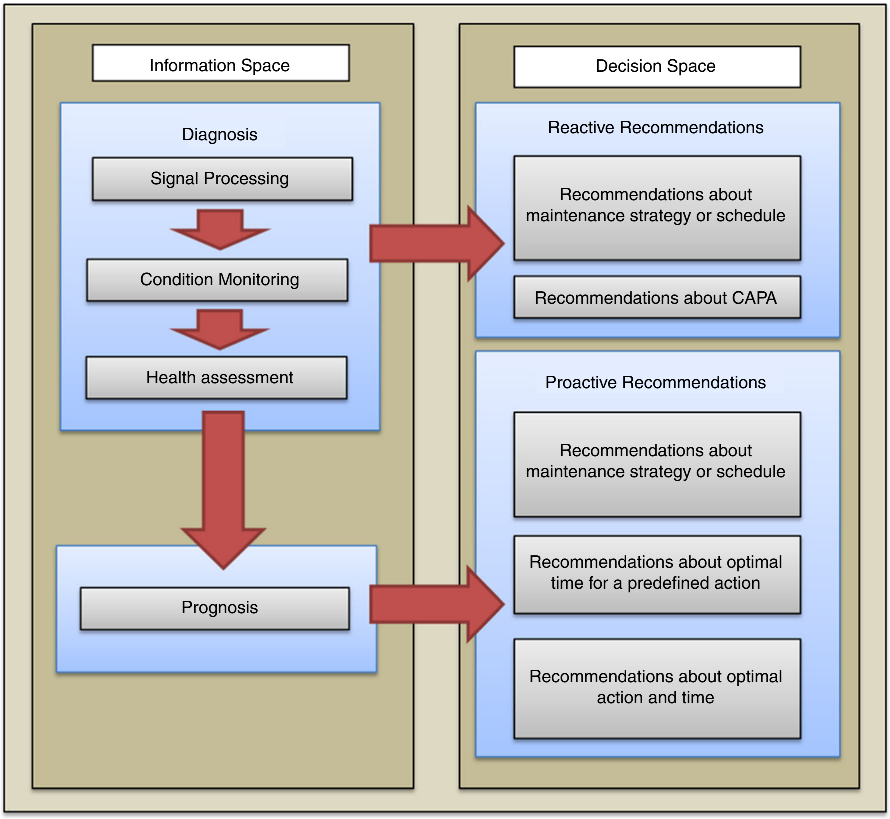


Figure 6.
Framework for decision making in maintenance

In the general case, all steps shown in Figure 6 should be followed; however there may be limitations regarding the availability of data, which may hinder some steps. For example, if there is no list of actions and their mapping to types of failures or defects, or there is lack of other information regarding maintenance strategy or schedule, the framework can only provide prognostic information and cannot provide automated support for making decisions about the strategy, schedule or action.

Two main steps are included within the information space: diagnosis; and prognosis. Diagnosis involves a sequence of three sub-steps which represent the required analysis of the raw sensor data that are gathered until the detection of the current equipment health state. These sub-steps are:

(1) Signal processing, which provides some initial and primitive computation of sensor data.

(2) Condition monitoring, which compares the results of signal processing data analysis with predefined features.

(3) Health assessment, which combines condition monitoring data and historical data in order to provide information about the actual health state of the system examined (fault detection).

In case of recommendations for reactive actions, the next step would be recommendations about CAPA or maintenance strategy or schedule. In other words, based on the information about the current health state provided by the information space, the decision space focusses on generating the recommendations for mitigating actions. Support for reactive actions should be embedded even within a proactive DSS, because there is always the possibility that an undesired event, which has not been predicted, occurs. In this case, diagnostic information should be provided and maintenance actions for immediate implementation should be recommended.

Having examined the health state of the system, a prognostic model should be developed in order to support proactive recommendations. The prognostic model combines the diagnostic information and historical degradation data and patterns leading to a failure as well as domain knowledge and represents progression of system health. Domain knowledge can be modelling wear stages, degradation threshold limit, failure mode effects and criticality analysis, root cause analysis, fault tree analysis, etc. For example, relationships between effects such as failure and malfunction, and sensor parameters such as temperature and vibration should be identified. In this way, predictions can be made for when a failure will occur, calculating probability distributions of the occurrence of undesired events (e.g. failure if no action is implemented, failure even though an action has been implemented, etc.) and/or providing early warnings.

The output of the prognostic model feeds into the proactive decision making process, which is represented by the Proactive Recommendations constituent of our conceptual framework's Decision Space. Proactive decision making utilizes domain knowledge (e.g. list of actions, time intervals for each possible action, cost function, etc.) and recommends the optimal maintenance strategy, the optimal schedule, the optimal time of applying a predefined action or the optimal action and its time of applying. The output of proactive decision making depends on the user requirements as well as the available data and knowledge and it ranges from generic (e.g. maintenance strategy or schedule) to specific recommendations (e.g. maintenance action and time of applying it).

Each step of the decision making framework shown in Figure 6 requires specific input and provides specific output which feeds into the next step. Input depends on the availability of the appropriate data and information and output can vary based upon the user's requirements, the method used and the taken input. Table III summarizes the input and output of each step of the decision making framework based on our literature review.

Our conceptual framework extends the existing works in CBM in two ways. First, it identifies the CBM constituents and organizes them in the Information Space and the Decision Space. The Information Space includes the diagnosis phase dealing with the provision of information about the current state of equipment, and the prognosis phase dealing with the provision of information about the future health state of equipment. This information supports informed decision-making about maintenance in the sense that it reveals issues that are not visible even by an experienced engineer.

Second, while the Information Space has been extensively researched, our literature review revealed that the Decision Space has not been investigated thoroughly. Therefore, we further analysed the decision support constituent according to the types of recommendations that can be provided. The latter have been separated in two types: reactive and proactive recommendations. Each one of these types has been further analysed according to the provided output as shown in Table III. Reactive recommendations deal with actions that are implemented after the occurrence of an undesired event (e.g. breakdown). We found out that these actions can involve either

	Input	Output
Diagnosis	*Sensor data* (about the measured parameter used as indicator of degradation) *Historical data* (about the measured parameter used as indicator of degradation till failure)	Current health state
Reactive actions	*Current health state* *List of actions* (that are integrated with the current undesired event) or predefined action or alternative strategies	Notification Recommendations about CAPA Maintenance strategy or schedule
Prognosis	*Current health state* *Sensor data* (about the measured parameter used as indicator of degradation) *Historical data* (about the measured parameter used as indicator of degradation till failure) *Threshold limit* (where a failure/ malfunction occurs) *Wear stages* (from domain knowledge) *Other domain knowledge*	Early warnings RUL and confidence level Probability distributions of the occurrence of undesired (e.g. failure, malfunction, etc.)
Proactive actions	*Early warnings* *RUL and confidence level* *Probability distributions of the occurrence of undesired events* (e.g. failure, malfunction, etc.) *List of actions* (that mitigate or eliminate the future undesired event) *or predefined action or alternative strategies* *Cost functions* (for the forecasted event and for the possible actions) Time intervals (delays) for each possible action	Early notification Recommendations about Maintenance strategy or schedule Optimal time for a predefined action Optimal action and time

Table III.
Input and output in each step of the decision making framework

the implementation of a CAPA (Qian *et al.*, 2008; Peng *et al.*, 2010; Ruiz-Mezcua *et al.*, 2011; Prakash and Ceglarek, 2013; Pal and Ceglarek, 2013; Pal *et al.*, 2014) or a change in the maintenance strategy or schedule. On the other hand, proactive recommendations are based on predictions about an undesired event (e.g. a future breakdown). We found out that proactive recommendations can be separated in three categories, according to their output which can be: a change in maintenance strategy or maintenance schedule (Muller *et al.*, 2007; Kaiser and Gebraeel, 2009; Aissani *et al.*, 2009; Besnard and Bertling, 2010; Besnard *et al.*, 2011), the optimal time of applying a predefined action (e.g. replacement) (Wu *et al.*, 2007; Elwany and Gebraeel, 2008; Bouvard *et al.*, 2011; Castro *et al.*, 2012; Huynh *et al.*, 2012) or pairs of optimal actions and optimal time for their implementation (Engel *et al.*, 2012).

5. Practical demonstration of the proposed framework

In this section we present a practical application of the proposed proactive decision making framework for CBM in the oil and gas industry. We describe the practical role and use of the proposed framework focussing on how it can support proactive decision-making ahead of time on the basis of real-time observations and predictions about future undesired events, through a real maintenance scenario.

CBM in the oil and gas industry employs various monitoring means to detect deterioration and failure in some critical drilling equipment. In our example, we focus on the gearbox drilling equipment and consider as indicators the rotation speed of the drilling machine's main shaft in Rounds Per Minute (RPM), along with the lube oil temperature of the drilling machine's gearbox. Temperature sensors gathering real-time data in a high frequency (every 20 ms), along with historical data of oil temperature, RPM events and gearbox equipment failure, are used for assessing the health state of the gearbox in real-time (see Figure 6). The high frequency of the real-time data requires a Big Data infrastructure and an appropriate architecture (e.g. EDA). Diagnosis step identifies that a drilling gearbox equipment failure starts to occur and, therefore, informs about its actual health state (e.g. anomalies detection).

The prognosis step involves the usage of statistical/machine learning methods to build a prognosis model of the equipment health offline, as well as the online prediction of gearbox's RUL along with the probability distribution function of the gearbox breakdown by using methods such as Bayesian networks, neural networks, etc. The prognostic output (e.g. a specific exponential probability distribution) is needed as input for the proactive decision making process accompanied with a list of alternative maintenance actions (lube oil change, system restart, lower pressure, full maintenance), the cost of each action as a function of time, the cost of gearbox breakdown, the time of next planned maintenance and the RUL after the implementation of each action. A recommendation about the optimal action and the optimal time for its implementation is provided by employing decision making methods such as MDP. In this way, the oil and gas company is able to know which action to do and when. To eliminate the risk that an undesired event, which has not been predicted, occurs, the company has also defined based on domain knowledge, a list of reactive actions in the form of IF-THEN rules.

In this way, the company is guided about how to utilize its sensors and historical data as well as its domain knowledge in order to improve its maintenance management business process and turn from reactive to proactive for the improvement of its efficiency.

6. Discussion

Although decision making methods based on predictions about the health state of the equipment has been proposed in the last years, not all of the capabilities of proactive computing have been exploited. The proposed framework allows embedding in the CBM concept e-maintenance capabilities in conjunction with proactive decision making in order to allow the provision of more detailed recommendations. In this way, the decision maker is based less on his/her personal judgement and is able to take proactively informed decisions. At the same time, the time window for taking decisions about how to resolve a problem is increased, as the decision epoch starts upon the prediction of the problem instead of upon its occurrence. So, on the one hand the probability of human error is decreased while, on the other hand, there is more time for planning and undertaking other manufacturing operations that are closely related to maintenance (e.g. logistics issues, such as the ordering of spare parts). Furthermore, based on the proposed framework, the optimal time for maintenance can be accompanied with the appropriate action according to the predictions, the user requirements and the company policies. Therefore, the higher the level of proactivity is achieved, the more efficient the maintenance becomes, because undesired events are eliminated or mitigated and all the business functions that are related to maintenance, such as production, ordering of spare parts, etc., operate seamlessly.

The systematic formulation of CBM strategy in the proposed framework enables its embodiment to an information system for the full exploitation of proactive decision making in the context of CBM. In this sense, the proposed framework is not only a systematic representation of a maintenance management business process but also the basis for the development of a DSS for CBM that gathers and analyses real-time sensor data, provides diagnostic and prognostic information and automates proactive decisions by providing recommendations about maintenance in a proactive manner. Real-time data are gathered in a high frequency, so several challenges regarding Big Data need to be addressed by applying innovative technologies. EDA can significantly enable the processing of Big Data, so that predictions are provided when an anomaly detection event is received and recommendations are generated when an undesired event (e.g. breakdown) is predicted. As the decision space of the proposed framework has been structured according to the types of recommendations that can be provided, a DSS that is built upon it will be able to support proactive decision making for CBM in various application domains and for a wide range of functional and non-functional application requirements. Provision of reactive recommendations should be also made available because the probability that the DSS fails to predict an undesired event cannot be completely eliminated; in that case immediate actions to handle the undesired event should be recommended.

The focus of the literature search and the whole analysis was on proactive decision making rather than reactive and consequently, on data-driven prognosis and proactive recommendations. For this reason, the literature for methods dealing with the three sub-steps of Diagnosis has not been examined in detail.

7. Conclusions and future work

Our literature review of CBM methods indicates that there are combinations of machine learning and decision making methods used in order to provide recommendations based on predictions. These predictions are derived from the analysis and processing of real-time sensor data. For each paper examined, the methods as well as their inputs and outputs were identified. Based on previous research works regarding modeling CBM concept and on the literature review of methods and techniques that are used for prognosis and decision making, a framework for maintenance decision making is proposed. This framework enriches others existing in literature by structuring the information and the decision space and by focussing on the latter. Moreover, the proposed framework embeds the concepts of proactivity and e-maintenance to CBM in order to enable the provision of timely and reliable recommendations. Finally, reactive actions for immediate implementation based on diagnostic information are recommended when an undesired event that has not been predicted occurs.

Although there are many research works dealing with predictions, e.g. about RUL, only few propose methods to utilize this real-time prediction accompanied with expert knowledge to provide maintenance recommendations. More combinations of methods can be developed by using machine learning methods that have been used in literature for prediction of RUL with various decision methods so that they are extended in the Decision Space of the framework proposed. Furthermore, decision methods in existing literature do not exploit all the possibilities for proactive decision making, for example by providing the most appropriate maintenance action and the optimal time for applying it, while, they are not usually considered as part of a wider framework for decision making in CBM.

Based on the proposed framework, we plan to develop a DSS which will provide proactive maintenance recommendations according to user requirements. Then, we will examine the possibility of using context-awareness so that data are enriched and recommendations take into account the various conditions that may affect them.

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