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## On a Predictive Maintenance Platform for Production Systems

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Maintenance and support may account for as much as 60 to 75% of the total lifecycle cost of a manufacturing system. This paper presents a review on the predictive maintenance approaches, methods and tools in manufacturing systems and proposes an integrated predictive maintenance platform. This platform consists of three pillars, namely data acquisition and analysis, knowledge management, and a sustainability maintenance dashboard. The first pillar is responsible for data extraction and processing, the second one focuses on the maintenance knowledge modeling and representation and the third pillar provides advisory capabilities on maintenance planning with special emphasis given to environmental and energy performance indicators.

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**1. Introduction**

During the last years, cost and time have been the basic drivers of manufacturing systems, whilst ensuring that reliability, safety and integrity are not compromised [1]. Manufacturing systems maintenance is becoming increasingly important, since in many industrial plants, the maintenance costs often exceed 30% of the operating costs and in the context of manufacturing systems lifecycle, maintenance and support, account for as much as 60 to 75% of the total lifecycle costs [2]. The present systems do not provide a systematic and structured way of modeling and integrating early failures in the associated maintenance activities. Although advanced systems or subsystems are built, with real-time monitoring capabilities, the data when collected are not organized and analyzed and in the end, correct predictive maintenance actions cannot be enforced. The visualization of the operation data that could lead to a better analysis for preventive maintenance is rather simplistic with the use of 2D images and typical charts, lacking in a user friendly interface that facilitates the engineer's understanding.

**2. Industrial Practice and Academic Approaches**

Advanced maintenance technologies that increase the sustainability of production systems have not been well implemented in industry yet [3]. Within the current section, the existing approaches, tools and models on the following areas are presented: i) Condition Based Maintenance, ii) Environmental Assessment of Production Systems, iii) Results Visualization and iv) Integrated Maintenance Platforms.

**Condition Based Maintenance.** The occurrence of unscheduled maintenance can introduce costly delays and cancellations if the problem cannot be rectified in a timely manner. Condition-based maintenance (CBM) is a program that recommends maintenance actions, based on the production system's status. The CBM utilizes prognostics methods and is considered being more efficient without losing its reliability in comparison with the planned maintenance regarding cost [4]. A CBM program consists of three key steps: 1) Data acquisition step (information collecting), to obtain data relevant to system health, 2) Data processing step (information handling), to handle and analyze the data or signals collected in step 1 for better understanding and

interpretation of data, 3) Maintenance decision-making step (decision-making), to recommend efficient maintenance policies [4].

The maintenance decision making step can be further analyzed into two sub-steps, in particular, the diagnostics and the prognostics. Diagnostics deal with the identification and the quantification of the damage that has occurred, while prognostics involves the prediction of the damage that is yet to occur [5][8]. Diagnostics include :i) fault detection, ii) fault isolation and iii) fault identification, while prognostics comprise i) remaining useful life (RUL) prediction and ii) confidence interval estimation. Fault detection is responsible for detecting and reporting an abnormal operating condition, fault isolation is concerned with the determination of the component that is failing or has failed and fault identification deals with the estimation of the nature and the magnitude of the fault. The remaining useful life prediction attempts to identify the lead time before a failure criterion is reached, while the confidence interval estimation attempts to quantify the confidence interval of the RUL prediction.

Data acquisition is the process of collecting and storing data from the targeted assets for the purpose of maintenance. The collected data can be classified into two main categories: i: event data and ii) condition monitoring data. The first category includes data concerning the information as to what happened (e.g. breakdown and what the causes are) and what was done (e.g. repair) to the targeted physical asset. Condition monitoring data are the measurements (e.g. pressure, temperature) of the parameters related to the health condition of the physical asset. Data processing includes two main steps, namely data cleaning and data analysis. Data cleaning is responsible for removing errors and noise from the retrieved data. Data analysis involves methods, such as time domain analysis, frequency domain analysis and event data analysis. Autoregressive moving average (ARIMA) models are used quite extensively as a time domain analysis technique [6]. In [7], an AR model is used in order to model vibration signals, collected from an induction motor. Principal component analysis used in the case of gear fault diagnosis or pseudo-phase portrait [9] and the correlation dimension technique [10]. The proportional hazards model (PHM), belonging to event data analysis, aims to relate the failure probability to both age and condition variables, so that one can assess the failure probability with given machine condition at any specified age. In [11], a PHM model has been developed for the failure and diagnostic measurement data analysis from bearings.

Machine fault diagnostics is a procedure of mapping the information, obtained in the measurement space and/or features in the feature space to machine faults in

the fault space [4]. The hypothesis test is a method used quite often in diagnostics [12][13][14]. Cluster analysis is another statistical approach that classifies group signals into different fault categories, based on the similarity of their characteristics. The AI approaches have been increasingly applied to machine diagnostics and it seems that the AI approach outperforms the conventional ones. Neural networks (NNs), in particular, the feedforward NN (FFNN) structure is widely machine fault diagnosis [14]. Applications of ES to fault diagnosis are further analyzed into rule based reasoning systems [15], case based reasoning ones and model based reasoning systems. The NNs store knowledge by training on observed data with known inputs and outputs, while ESs utilize domain expert knowledge in a computer program with an automated inference engine [16][17]. Model based approaches are mathematical descriptions of systems based on physics specific. Such methods have been implemented for systems such as gearboxes, bearings, rotors and cutting tools [18].

The main objective of prognostics is the prediction of the time left before a failure occurs (or, one or more faults) given the current system condition and the past operation profile. The main approach widely used in prognostics is concerned with the estimation of the remaining useful life (RUL). RUL approaches are classified by [4][5] into four main categories: a. knowledge based, b. physical models, c. artificial neural networks and d. life expectancy. The knowledge based models store past defined failures in a database. In case of a new event, they retrieve from the past, the most similar observation, related to a failure, and the life expectancy of the asset is deduced. The knowledge based models are further classified into expert and fuzzy systems. The artificial neural networks estimate the remaining useful life of an engine directly or indirectly, by training an ANN [16][17][19][20] with past observation data of failure events. The physical models provide an assessment of the RUL, based on a mathematical representation of the physical behaviour of the degradation process. Finally, life expectancy models [19] determine the time left of an asset or an asset's component with reference to the expected risk of deterioration, under known operating conditions.

**Environmental Impact and Energy Costs Assessment.** Energy is today the key to economic growth, and in turn, fossil fuels are still the key to energy production worldwide. Manufacturing activities may involve significant energy consumption. Furthermore, transforming raw materials into consumer products may be also a source of environmental pollution. Waste coming out from manufacturing activities is an environmental threat, originating from several regions around the world. In general, manufacturing waste involves a very diverse group

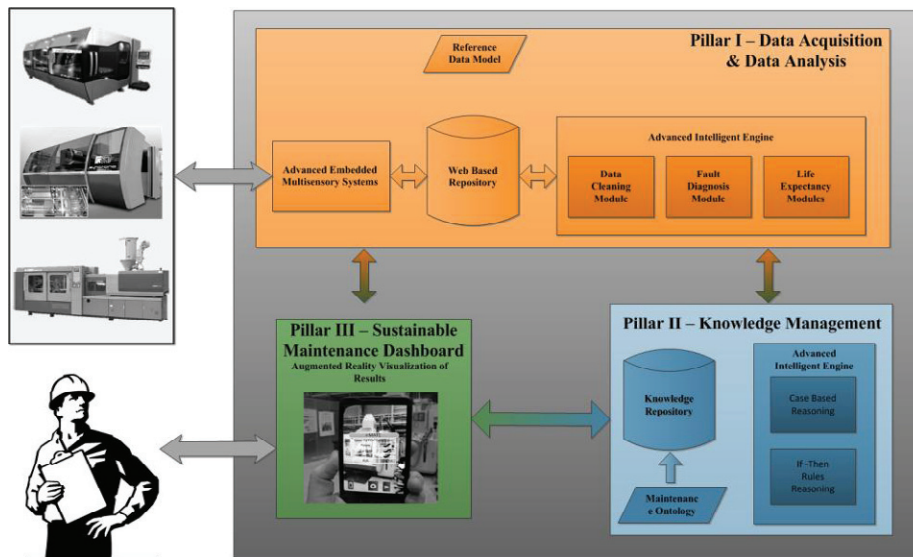


Fig. 1. Architecture of the proposed platform

of substances, due to the vast range of products produced and processes involved. The waste generated depends on the technology used, the nature of the raw material processed and the quantity that is discarded at the end of the chain. Since the production of goods keeps constantly increasing worldwide, the greenhouse gas emissions from all the major fuels are also on the increase [21].

**Visualization of Maintenance Results and Activities.** Augmented Reality refers to a predominantly real environment enhanced by the addition of virtual content. The AR technology provides the means of merging a richly layered, multi-modal, 3D virtual experience into a real environment [22]. Regarding maintenance, there has been research, concerning the insertion of AR into the processes of production and manufacturing [22][23][24]. A Collaborative Virtual Reality Environment, was developed by combining several degrees of information sharing, 3D visualization and real world user-interaction metaphors. In [24], a Collaborative Manufacturing environment was conceptualized and was designed based on an open architecture, whilst a browser-server technology had three layers which were data, business and presentation layer. In [25], the authors describe a method of process planning through the use of a tool that allocates AR data according to assembly processes. It is important to state that in the last case, the links that the planner creates between the product resource and the operation are automatically identified by the tracking information.

**Integrated Platforms.** During the past years, several attempts have been made for the development of platforms that address all the steps of the condition

based maintenance, for a series of equipment, from sensors and data gathering up to maintenance decision making. CASIP (Computer Aided Safety and Industrial Productivity) is an industrial maintenance platform for manufacturing, enabling remote access and mobile technologies, developed by PREDICT [26]. The TELMA platform is built on the industrial CASIP product and encapsulates the development of a prognosis process within e-maintenance [27] and it is based on a combination of a probabilistic approach for a system degradation mechanism modeling along with an even based method of dynamical degradation modeling. Another platform [28] follows the basis of a reference model for fault management systems, capable of performing preventing maintenance plans, fault detection & isolation and diagnosis tasks. This approach utilizes a multi agent system, in particular, MAS-CommonKADS [29] and as a reference framework the AIDCS (Agent-based Intelligent Distributed Control System) was used. It is found that few researchers use mobile devices, especially PDAs with embedded technology and even fewer with Web technology [29][30]. Moreover, very few platform that remain at research level can address all the layers of condition based maintenance, while the industrial Computerized Maintenance Management Systems do not provide prognostics of high accuracy through the utilization of advanced Artificial Intelligence approaches.

**Data Acquisition and Analysis.** The existing sensory systems are rather simple, without offering intelligent functionalities, and online data sharing. There is a need for advanced multi sensor techniques, capable of robust on line data acquisition. Moreover, the quality of

measurements is significantly affected by the sensor noise, the disturbances and the instrument degradation. Physical models of equipment degradation provide high accuracy, whilst on the other hand, they are expensive and their application field is rather narrow. Stochastic models such as ARMA are not capable of capturing non stationary processes, while regression models do not accommodate random shocks.

**Knowledge Management.** Fault detection demands highly skilled and trained personnel, thus automatic fault detection is required. Knowledge deriving from past failures is not systematically stored, thus, in terms of time and cost, it cannot be easily retrieved, especially during the early design steps of a system. Rule based expert systems face the problem of combinatorial explosion when the number rule increases exponentially as the number of variables increases.

**Maintenance Environmental Assessment, Planning and Visualization.** An assessment of maintenance environmental impact and energy costs is not fully addressed by the existing approaches. Maintenance planning systems focus on scheduled based maintenance; they are not capable of multi-criteria decision making and do not take into consideration the environmental impact. There is poor visualization of the environmental impact of manufacturing. In general, diagrams related to maintenance and failures are difficult to be represented due to their increased complexity. Smartphones and mobile devices are not yet fully exploited in an industrial environment for equipment characteristics overview. Finally, the existing CMMS do not integrate data acquisition, data analysis, diagnostics, prognostics, visualization, environmental assessment and maintenance activities planning.

### 3. Proposed Platform

The current approach envisions the development of a platform that would be supporting designing systems for reliability, fault detection, degradation capturing, maintenance activities planning, and visualization of complex data and information. The proposed platform consists of three main pillars that are further analyzed and presented in Figure 1. *Data Acquisition and Analysis:* this pillar is responsible firstly, for gathering and storing data utilizing advanced multi embedded sensors and a web repository and secondly for analyzing the data in order for any possible deviation from the nominal condition to be detected. *Knowledge Management:* this pillar aims to promote the fault diagnostics and the efficient storing of past knowledge of failures via the semantics technology. The Knowledge Management pillar consists of the ontology that is the main scheme for the knowledge repository and the advanced inference engine. *Maintenance Dashboard:*

this pillar addresses the need for a user friendly and intuitive presentation of maintenance critical data that will support maintenance engineers in their decision making.

**Data Acquisition and Analysis.** The Advanced Multi Embedded Sensory Systems will address the need for intelligent sensors with capabilities of noise reduction, multi parameter monitoring and online data sharing. The proposed platform will implement sensor systems with multiple sensing abilities, miniature size and light weight, low power consumption, long range and high rate data transmission, large onboard memory, fast onboard data processing, low cost, and high reliability. The Advanced Intelligent Engine is capable of performing fault detection and degradation capturing. Fault detection, deviation from the nominal condition, is performed by employing Symbolic Dynamic Filtering (SDF). The SDF is a statistical pattern recognition method for studying dynamical systems. In particular, reference time series, stored in the repository, and the timeseries acquired by the sensors are compared and analysed with SDF [6]. The SDF outperforms other methods in terms of robustness to measurement noise and spurious signal while the SDF is more adaptable to low resolution sensing, due to the coarse graining in space partitions [6][31]. The SDF is more robust to measurement noise and spurious signal. Secondly, the SDF is more adaptable to low resolution sensing, due to the coarse graining in space partitions [31]. The SDF can also be a part of a real time Fault Detection and isolation process, which provides the opportunity of the same data and methods on different processes to be utilized. Advanced Intelligent Engine will be capable of degradation capturing. Degradation capturing will be performed with the use of life expectancy models, in particular, ARIMA models. The ARIMA models will estimate the remaining useful life of advanced equipment. The RUL refers to the time currently left before a certain failure criterion is reached. The Advanced Intelligent Engine will include a list of failure criteria closely related to the equipment's parameters that are monitored with the help of the sensors. Apart from estimating the values of the monitored parameter, the relevant confidence intervals, with the upper and lower forecasting limit, are also estimated. *Reference Data Model and Web based Repository* are responsible for the data storing, retrieved by sensors. The reference data model includes data required by all the phases of the condition based maintenance. The Data model provides the data scheme and the main properties of the data. The Web-based Repository allows engineers to access maintenance equipment data from remote places.

**Knowledge Management.** The components of this pillar are the ontology, the knowledge repository, the advanced inference engine and the design for reliability.

The scope and the key functionalities of each component are further analyzed hereafter. Ontology will define the entities, and their relationships, involved in the design for reliability, maintenance diagnostics, prognostics and maintenance planning. In conclusion, the ontology implemented in OWL will provide: i) a representation of fault characteristics, monitored parameters and their relationships, ii) a semantics enriched matching of failures with possible causes and solutions, iii) a classification of past failures based on their characteristics, iv) a mapping of all the case based maintenance steps including visualization, environmental assessment and maintenance activities planning and v) a mapping of all the case based maintenance steps including visualization, environmental assessment and planning of maintenance activities. The Knowledge repository's primary objective is ontology storing. Semantics based technologies will be utilized for the development of the repository. The Knowledge Repository will be synchronized with the Web-based Repository in order to share the same data. Moreover, the KR will store the rules as they will be defined by the Advanced Inference Engine (AIE) and will allow the extraction of knowledge from its contents by utilizing again AIE, implementing it with the Java Technology and the Jena Framework [32]. The Advanced Inference Engine envisions to perform accurate and reliable diagnosis, providing fault identification and isolation, indicating the possible cause of the fault as well as a solution. The Advanced Inference Engine is responsible for the definition and the discovery of new knowledge by utilizing rule based mechanisms and case based reasoning approaches. A rule based system, utilizing the concepts described by the ontology, will allow the formation of rules that will associate a series of deviations from the nominal condition with the specified faults, their causes and possible solutions. Thus, the rule based system, will allow the systematic storing of failures and their solution. Moreover, this system will provide an automatic diagnosis of failures with the use of the stored rules and performing rules reasoning. Apart from the rule based system, diagnostics will also be supported by a case based reasoning. Similar to the rules, the elements of the cases will also be defined by the ontology. Past failures are described as cases and are stored in the repository. In the occurrence of a new failure, a similarity mechanism performs a systematic search in order to find the closest match case. This case is then retrieved and its solution, after the proper modification, is proposed for the new failure.

**Sustainable Maintenance Dashboard.** Visualization has as main scope the presentation of diagnostics, prognostics and planning diagrams, data in a user friendly and intuitive way, facilitating the engineer to

have a quick insight of the maintenance problem, cause, solution and planning. The proposed platform is expected to visualize results and performance indicators, such as the environmental impact, the remaining useful life, cost indicators, utilizing augmented reality technologies. In particular, with the help of augmented reality, the engineers can use simple gestures with smart-phones and have an overview of the data. Maintenance engineers can walk through the factory and have an overview of the maintenance characteristics of each equipment. Tools such as smartphones have a low cost, and are easy to be handled by engineers even in a shop floor environment. Environmental Maintenance Planning envisions tackling the complex task of maintenance activities scheduling optimizing cost, time, reliability and environmental criteria. The alternative schedule that presents the highest satisfaction of the aforementioned criteria will be produced and a Gantt chart of the maintenance activities will be available.

#### 4. Conclusions and Outlook

Multi-sensory intelligent systems capable of numerous parameters monitoring will be implemented under the proposed platform. The increased quality of retrieved data is guaranteed by the sensory systems of advanced accuracy and the noise removal, achieved by the following symbolic dynamic filtering approaches (SDF). The SDF outperforms the existing methods used in data analysis for noise removal. So far, the SDF has been utilized only in the fault diagnostics of aircraft engines [31]. The ARIMA models are capable of modeling non stationary processes, since they also include the "integration" part while at the same time, accommodate random shocks, in contrast to simple regression approaches [19]. Reliability and maintenance considerations take place during the early design steps by utilizing past failure knowledge, stored in the knowledge repository in the form of failure templates, described by the ontology. The design of equipment, processes and systems, taking into account maintenance and reliability parameters is covered by the proposed approach. Reasoning mechanisms, IF-Then Rules, and similarity measurements, provide a systematic and automatic way for the detection, identification and isolation of failure without requiring skilled personnel. Parameters deviations are connected with the fault types, their cause and a possible solution. All the aforementioned relationships are modeled with the knowledge mechanisms, i.e, ontology, inference rules and in terms of time and cost, they are efficiently and automatically retrieved. Scheduled based maintenance is by condition a based maintenance by utilizing prognostics tools, specifically remaining useful life. Thus, only necessary maintenance activities take place at

the time defined by the condition of the equipment. The maintenance planning engine takes into consideration the following indicative criteria i) environmental impact (scrap, CO<sub>2</sub> emissions etc), ii) energy costs, iii) energy efficiency, iv) energy efficiency, v) remaining useful life, vi) operating costs, vii) maintenance time (repair time, setup time). The augmented reality technology will allow a user friendly presentation of the results of maintenance activities that are described by high complexity. Specific interfaces will facilitate the overview of the key performance indicators that are critical for the maintenance activities. The proposed platform will utilize smart phones and mobile devices in general, in order to for them to be used in the shop floor by the maintenance engineers that would allow them to have an overview of the maintenance analysis results in a timely and cost efficient way.

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