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On a Predictive Maintenance Platform for Production Systems

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Abstract

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.

Keywords: Predictive Maintenance; Prognostics; Knowledge Management

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

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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], cased 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