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PREDICTIVE MAINTENANCE – A MAJOR FIELD FOR THE APPLICATION OF COMPUTER AIDED SYSTEMS

Abstract

Predictive maintenance is a widely applied maintenance program that requires extensive support of computer aided systems. The program uses specific procedures that are to be addressed when developing predictive maintenance software solutions. Despite the fact that software solutions for predictive maintenance were introduced almost at the same time as the program emerged, it still remains a very actual field for the application of computer aided systems. The practice also shows that developers of computer aided systems for predictive maintenance constantly encounter problems, trying to translate predictive maintenance procedures into the computer language. These procedures are very specific and require microprocessor-based equipment and development of sophisticated algorithms. Therefore, there is a distinct need for better awareness about the predictive maintenance concept among software developers.

The article aims to describe the essence of the predictive maintenance concept, its fundamental approaches and the main physical processes upon which the predictive maintenance procedures are based: (1) distinct vibration frequency components which are inherent in all common failure modes; and (2) constant amplitude of each distinct vibration component. The importance of the awareness with the concept for computer aided systems developers is emphasized. And the most problematic areas of software application in predictive maintenance programs are outlined, namely the development of effective computerized systems to capture and analyze an immense quantity of data (big data processing), and the development of systems, supporting an intelligent connection of smart devices with the means of internet protocols (Internet of Things).

***Key words*:** prognostics, vibration frequency components, mechanical equipment, Fast Fourier Transform, signal processing, big data, internet of things.

Introduction

Predictive maintenance is the new-age philosophy that gives managers outstanding means for the most efficient and effective operation of their plants. This is a technique for creating a more sustainable, safe, and profitable industry [13]. From visual inspection, which is the oldest method, yet still one of the most powerful and widely used, predictive maintenance has evolved to automated methods that use advanced signal processing techniques based on pattern recognition, including neural networks, fuzzy logic, and data-driven empirical and physical modeling [7, p. 3480].

Literature review. The concept was introduced more than two decades ago, however the research shows that there are still many manufacturing companies who do not seem to have adopted this approach or at least to be on the way for its acceptance [2, 6]. Despite advances in predictive maintenance technologies, time-based and hands-on equipment maintenance is still the norm in many industrial processes [7]. Additionally, when trying to implement the concept and adopt better maintenance processes, practitioners encounter other problems, such as the lack of data, needs to handle lots of data to perform precise estimations. Companies hardly have an overview of available data and appropriate modules, which are needed for a holistic predictive maintenance strategy [2]. The dominant reason for this ineffective management is the lack of factual data to quantify the actual need for repair or maintenance of plant machinery, equipment, and systems. Maintenance scheduling has been, and in many instances still is, predicated on statistical trend data or on the actual failure of plant equipment [5]. As we see, the nature of the concept is heavily dependent on the data acquisition and processing, therefore computer aided systems have been deeply involved into the realization of the concept since the very start.

There is indeed a lot of software solutions for predictive maintenance in the market, but at the same time developers are constantly struggling to overcome new challenges when trying to address predictive maintenance procedures. These procedures should take into account two main aspects: the hardware specification and the software format of the data [11, p. 3]. Existing market solutions do not provide all these capabilities as a holistic solution [14].

In order to address the challenges, software developers must put some effort to understand, at least to some extent, the essence of the predictive maintenance concept and the underlying physical processes that define predictive maintenance procedures. Additionally, physics-based approaches require extensive theoretical knowledge about the systems and their components to be analyzed. This knowledge includes deductive and expert knowledge as well as empirical values [2].

Investigation object. The above-mentioned facts point out that the predictive maintenance concept still represents a very actual field for the application of computer aided systems. The concept therefore calls for further research and better awareness among both, computer science academicians and practitioners dealing with the real-life software products development. The physical processes as well as predictive maintenance program procedures act as investigation objects for this article.

Investigation subject. Software development methods and approaches to address predictive maintenance procedures.

Article goal. The article aims to consider the theoretical background of the predictive maintenance concept, bring some information on techniques and procedures that are used in predictive maintenance programs, and outline potential areas of focus where computer aided systems may receive further development.

Discussion of the obtained results

1. The essence of the concept and its main procedures

In its very nature, the predictive maintenance concept is prognostic, and prognostics involves the prediction of the damage that is yet to occur [18, 21]. Predictive maintenance is a condition-driven preventive maintenance program. Instead of relying on industrial or in-plant average-life statistics (i.e., mean-time-to-failure) to schedule maintenance activities, predictive maintenance uses direct monitoring of the mechanical condition, system efficiency, and other indicators to determine the actual mean-time-to-failure or loss of efficiency for each machine-train and system in the plant [5, p. 5].

Predictive maintenance raises new challenges and allows a maintenance expert to investigate and make use of opportunities that could not be exploited before. Predictive maintenance actions are anticipative in nature, which allows a maintenance expert to consider non-already-planned maintenance actions [1]. The concept is very important in Product Lifecycle Management. It can help manufacturers to determine the condition of in-service product in order to predict when maintenance should be performed. Predictive maintenance is believed to be an effective way to save cost and time, and to avoid unexpected equipment failures in manufacturing [4, p. 385]. The basic rule of predictive maintenance is that if the abnormal events parameter value of the product reaches a certain threshold, it should be replaced or repaired [4, p. 388].

Predictive maintenance rests upon two fundamental things:

1. It is possible to identify and isolate the distinct vibration frequency components which are inherent in all common failure modes.

2. The normal operating dynamics of the mechanical equipment is characterized by constant amplitude of each distinct vibration component. If the operating dynamics changes, so does the amplitude.

The main technique used to collect data on these variables is vibration signature analysis. “Most comprehensive predictive maintenance programs use vibration analysis as the primary tool. Since the majority of normal plant equipment is rotating, vibration monitoring provides the best tool for routine monitoring and identification of incipient problems” [15]. To support this main analytical tool, predictive maintenance uses also four additional nondestructive techniques:

- process parameter monitoring (vibration monitoring);
- thermography;
- tribology;
- inspection.

Each technique has its unique set of indexes that help managers determine the actual need for maintenance.

The primary focus of analysis under predictive maintenance approach is the system. This means that the predictive maintenance treats equipment not as a set of separate gears (such as pumps, gearboxes, etc.), but as a complex whole that generates capacity, and in the end, the revenue and bottom-line profits for the plant. Strictly speaking, the variations in system variables, like load, speed, product, or instability on the individual component, are usually the root-cause of the major mechanical problems.

Moreover, in order to obtain utmost benefits from predictive technologies, the process parameters should be also taken into consideration. Such parameters like temperatures, retention time, flow rates, etc. define the operating envelope of the process and are integral components of the system operation.

The predictive maintenance program first addresses those systems on which the plant relies to produce revenue. It does not mean at all, that auxiliary equipment is completely ignored, it means that the highest degree of attention is paid to the most important systems.

2. Measurement Points

The main tool of the process parameter monitoring, that predictive maintenance utilizes, is the Fast Fourier Transform frequently referred to as FFT (fig. 1). Predictive maintenance programs use Fourier analysis or spectrum analysis to deconstruct a signal into its individual sine wave components. The result is acceleration/vibration amplitude as a function of frequency, which lets perform analysis in the frequency domain (or spectrum) to gain a deeper understanding of a vibration profile [8].

The FFT signature (or frequency domain signature), obtained at every measurement point, represents the motions of an individual machine-train component. Therefore, knowing the specific location and orientation of a measurement point is critical for correct identification of incipient problems. In other words, the FFT signature is a visual capture of the mechanical motion of a machine-train component, that considers specific direction/orientation and specific time and spatial points.

The collection of data during a vibration-monitoring process is quite complex, it is performed with the microprocessor-based equipment, and requires that a detailed database, containing data collection and analysis parameters, should be developed before the actual measuring begins. One important term, namely – narrowband (fig. 2), is normally also considered before starting the process of measuring. This term is used to define a specific frequency range that must be monitored with particular attention, because the machine characteristics in this range are of high probability to cause a potential problem.

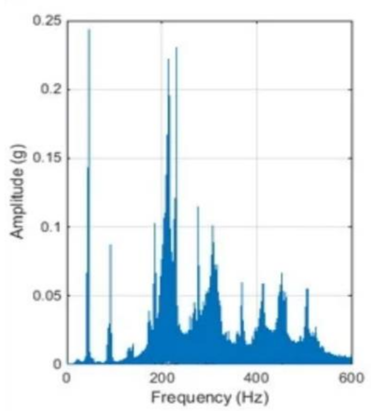

Fig.1. Fast Fourier Transform
Source: [8]

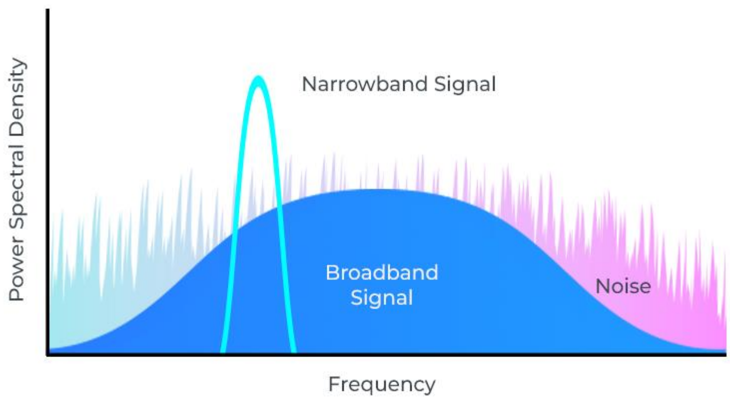

Fig. 2. Narrowband signal
Source: [16]

All the measuring points should be sequentially and consistently numbered starting from the first outboard driver bearing and finishing with the outboard bearing of the final driven component. This allows to immediately identify where a particular measuring point is located. Besides, to enable the analyst to consider all the parameters that affect each machine-train component, the measurement points must be grouped on a "common-shaft".

An essential part of a predictive maintenance program design is the identification of failures that can be prevented. Predictive maintenance analysts should strive to understand the mechanism of a component failure. The necessary inputs for understanding such a mechanism are occurrence frequency for each problem, combination of causes that led to that failure, and the analysis of what happens if failure takes place. The goal is to reduce those inputs or completely eliminate them. Criticality of a failure should be considered to establish the priority of efforts. The list of common failure causes is represented in the Table 1 below:

Table 1. Common equipment failure causes

Abrasion	Age deterioration	Consumable depletion	Corrosion
Friction	Puncture	Stress	Vibration
Abuse	Bond separation	Contamination	Dirt
Operator negligence	Shock	Temperature extremes	Wear
			Fatigue

Source: adapted from [5, pp. 219-223]

3. Relation to existing maintenance programs

Many existing traditional maintenance management methods are deemed to be very useful and have lots of benefits for performance improvement. But in fact, they just provide management with some data, having little or nothing to do with actual cost reduction, equipment availability improvement, or bottom-line profits increase. The unfortunate part is that too many programs are judged solely on the number of measurement points acquired each month, how many points are in alarm, or the number of unscheduled delays. As a result, a program is viewed as being successful even though it is actually increasing costs.

In contrast to traditional methods, the predictive maintenance program takes much more thorough approach. The approach is based on the following principles:

• the monitoring frequency should correspond to critical points. According to this, the proper monitoring frequency must be varied depending on the specific technology used and the criticality of the plant system;

• the personnel involved should have complete understanding of predictive maintenance technology. In addition, clear and comprehensive judgment criteria should be developed;

• focus on capacity – the most important success measure. This means that effective program implementation will result in a positive increase in percentage of non-defective production output. As opposed to capacity increase, the program cost is also to be kept in mind. This criterion should include all incremental cost caused by the program, not just the labor required to maintain the program;

• effective use of predictive maintenance technologies must strictly rely on ability to measure changes. Therefore, it is essential that the plant implements and maintains an effective plant performance evaluation program. Universal use of a viable set of measurement criteria is crucial;

• strong management commitment. Managers must have a complete understanding of predictive maintenance, particularly they must understand the absolute necessity of regular, timely monitoring cycles; the labor required to gain maximum benefits; or the need to fully use the information generated by the program.

Adhering to these principles provides the most cost-effective means to (1) evaluate the operating condition of critical plant systems; (2) establish a robust program plan; (3) create a viable database; and (4) establish a baseline value [17].

COMPUTER AIDED SYSTEMS FOR PREDICTIVE MAINTENANCE

One of the biggest obstacles for deployment of predictive maintenance, is a lack of systematic approach and clear implementation strategy. Companies hardly have an overview of necessary modules required for predictive maintenance, particularly software-based models. There is even greater uncertainty about how the individual modules can be combined in a targeted manner, or how the respective data can be used sensibly using suitable methods and software [2, p. 1744].

The consideration of the essence of the predictive maintenance concept allows us to define two main areas that present the biggest challenges for the development of computer aided systems. Namely these are (1) systems to capture and analyze an immense quantity of data (big data processing), and (2) systems, supporting an intelligent connection of smart devices with the means of internet protocols (Internet of Things). And indeed, nowadays these areas are actively discussed by practitioners and the interest in academic circles is constantly rising.

1. Big data

Although the concept of big data is not new, within the field of predictive maintenance it poses some important challenges that should be addressed by developers of computer aided systems. In this era of information, enterprise institutions should handle big data issues [14]. One of such challenges is the handling of immense data flows that are extremely complicated, since data comes from monitoring of real physical processes. With the course of time this aspect becomes more and more complex, but at the same time more and more important for organizations, especially for big production plants where a lot of equipment is deployed. “The main difference between big data and the standard data analytics that we’ve always done in the past is that big allows us to predict behavior. Also, predict events based upon lots of sources of data that we can now combine in ways that we weren’t able to before” [9, p.5].

As we stated in the previous section, “prediction” is the key term in predictive maintenance programs, therefore the better handling of big data is in place, the better maintenance program outcomes can be expected. There is an inherent risk that “prediction” brings with itself, because “prediction” requires understanding of underlying theory and mechanisms. And if we are talking about computer aided systems for predictive maintenance, the essence of this maintenance concept should be clearly understood, and software developers should put some effort to get at least basic knowledge in the field. This knowledge will later pay off when the software development starts.

For computerized maintenance systems the problem with big data becomes even deeper under the process of collecting information related to the different maintenance actions. For example, Ren and Zhao mark out the following two problems: (1) how to establish an overall big data capturing and integration architecture to sense and exchange the real-time data during lifecycle; (2) how to discover the previously unknown and potentially useful patterns and knowledge from big data [4].

Efthymiou et al. state that the present systems do not provide a systematic and structured way of modeling and integrating early failures in the associated maintenance activities – “very few platforms 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” [3]. This becomes particularly important when we start to consider the complete product lifecycle and realize that different stages of a product lifecycle require different information, and different approaches of getting it. As a result, actors involved in each lifecycle stages have made decisions based on incomplete and inaccurate product lifecycle information of other phases, which has led to operational inefficiencies [19].

As we see from the brief discussion above, predictive maintenance raises many challenges and calls for innovative concepts to handle big data. Probably introduction of new algorithms, establishing of new data mining technologies and programming libraries are the directions where computer aided systems should be headed to. The real-time decision-making methods on maintenance actions should be analyzed, advanced data flow models to implement the data-driven predictive maintenance decision-making should be presented. Discussions on data and knowledge sharing mechanisms should be started to investigate and make use of opportunities that are yet to be explored.

2. Internet of things

The big data challenge discussed in the previous section is closely connected with the concept of internet of things (IoT). IoT is a vision of an integrated network covering physical objects that are able to collect and exchange data [14]. Collecting usage data from different production equipment using an IoT platform is the main step in building a general, cloud based, predictive maintenance system, thus simplifying the factory upkeep [11, p. 1].

In more broad sense IoT can be defined as a network of physical objects—“things”—that are embedded with sensors, software, and other technologies for the purpose of connecting and exchanging data with other devices and systems over the internet [10]. The Internet of Things was described as the intelligent connectivity of smart devices by which objects can sense one another and communicate, thus changing how, where and by whom decisions about our physical world are made [12].

In the recent years the technology became very important and is being already actively applied in many industries. Big power plants and engineering corporations are not the exclusion, it appears that the technology shows very good prospects in the field of predictive maintenance. Today many companies are trying to implement the IoT concept into modern manufacturing systems [11, p. 3]. There is a need for advanced multi sensor techniques, capable of robust on-line data acquisition [3, p. 223]. It is believed the rapid development of information and communication technologies, especially wireless technologies such as radio frequency identification, sensors, and smart tags provides a promising prospect that enables companies to track and analyze product lifecycle data, and make efficient decisions without spatial and temporal constraints [21, 23].

Despite its promising prospects, the concept of the IoT poses a lot of problems that should be addressed by developers of computer aided systems. The main drawback of using the IoT technology in manufacturing systems is the communication (connection) between standard industrial devices and the web platforms [11, p. 1]. It appears very often that protocols of industrial communication are not compatible with contemporary communication protocols that IoT platform use. Therefore, new algorithms and methods of translation the industrial equipment language into the language, understandable for IoT devices should be developed and proposed.

There are three groups of components of a predictive maintenance program. These components are defined by data sources and physical processes they measure. The first group consists of sensors that measure "standard" physical process parameters such as level of pressure, temperature, etc. The second group consists of test-sensors measuring such equipment conditions as vibration and acoustic variances. These first groups of components are designed to measure "accompanying" process parameters, and the third group of sensors measures changes in the actual physical state of equipment, such as capacitance, inductance, insulation resistance, etc. In the most broad way, the integration of these three component groups is shown in the figure 3.

Each group of sensors generates its own set of signals/information flows that is vital for a successful implementation of the IoT concept. Many of the machines used in skilled trades or manufacturing are still not connected to IoT platforms because they lack sensors, software and connections to IT systems. IoT is proving to be a game-changer for many companies as a variety of industries begin employing IoT-enabled architectures and experimenting with how IoT solutions can bring new benefits [11, p. 7-8]. But still new methods for processes monitoring and data acquisition are to be introduced to enable successful implementation of the IoT concept in the field of predictive maintenance.

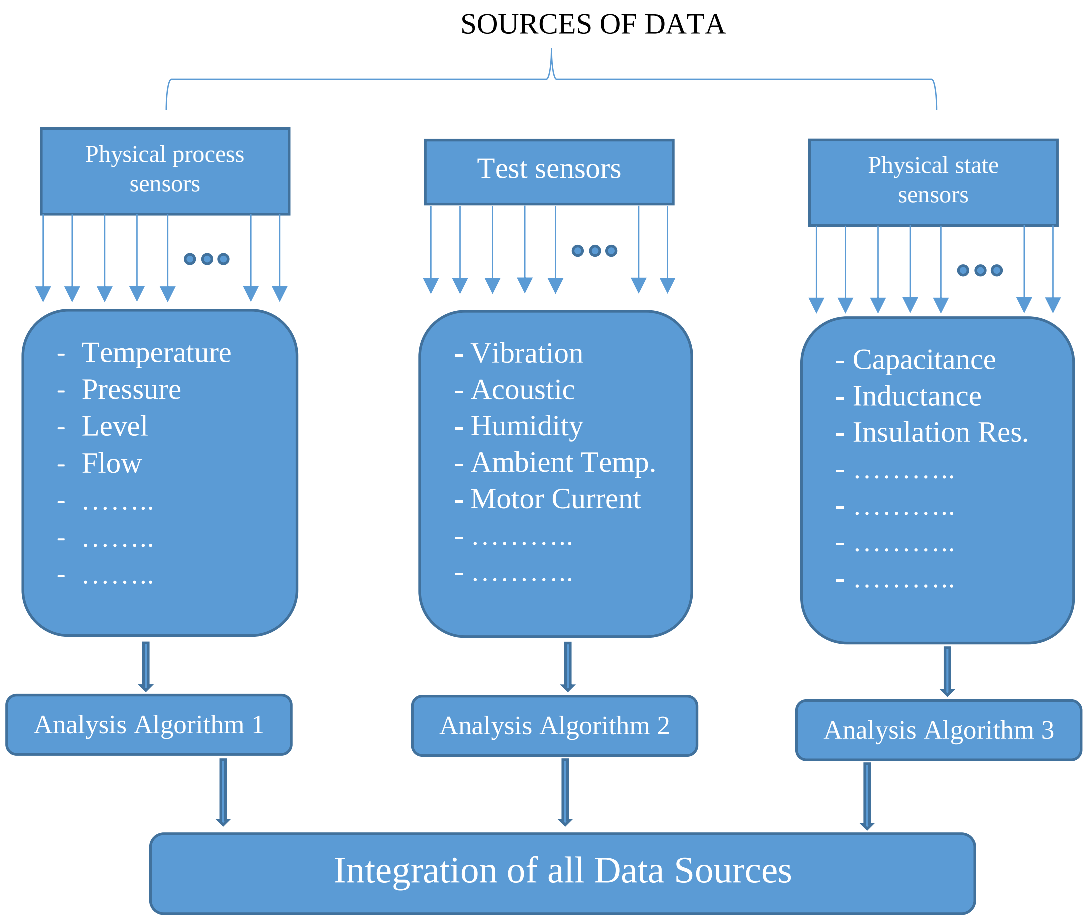

Fig. 3. Integrated system employing three groups of components of a predictive maintenance program
Source: adapted from [7, p. 3482]

Conclusion

Predictive maintenance is a major field where computer aided systems have been being applied. It uses Fast Fourier Transform as the main tool to monitor equipment conditions. The collection of data during monitoring processes is quite complex, it is performed with the microprocessor-based equipment, and requires that detailed databases and sophisticated software systems should be developed before the actual measuring begins. Therefore, it is suggested that software developers get acquainted with the predictive maintenance concept to facilitate successful development of computer aided systems for predictive maintenance.

Application of computer aided systems within the field raises two main challenges, namely (1) the development of effective computerized systems to capture and analyze an immense quantity of data (big data processing), and (2) the development of systems, supporting an intelligent connection of smart devices with the means of internet protocols (Internet of Things).

Introduction of new algorithms, establishing of new data mining technologies and programming libraries are the directions where computer aided systems should be headed to. The real-time decision-making methods on maintenance actions should be analyzed, advanced data flow models to implement the data-driven predictive maintenance decision-making should be presented. Discussions on data and knowledge sharing mechanisms should be started to investigate and make use of opportunities that are yet to be explored.

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ПРОГНОЗУЮЧЕ ТЕХНІЧНЕ ОБСЛУГОВУВАННЯ – ВАЖЛИВА СФЕРА ЗАСТОСУВАННЯ КОМП'ЮТЕРНИХ СИСТЕМ

Прогнозуюче технічне обслуговування – це програма догляду за обладнанням, яка широко застосовується на практиці, та потребує значної підтримки автоматизованих комп'ютерних систем. У програмі використовуються специфічні підходи, які повинні бути ґрунтовно інтерпретовані при розробці комп'ютерних рішень. Незважаючи на той факт, що програмні рішення були представленні майже відразу після виникнення концепції прогнозованого технічного обслуговування, ця сфера все ще заоишається актуальною для застосування автоматизованих комп'ютерних систем. Практика також показує, що розробники автоматизованих систем постійно стикаються із проблемами при намаганні інтерпретувати процедури прогнозуючого технічного обслуговування в комп'ютерні алгоритми. Ці процедури є доволі специфічними і вимагають мікропроцесорного обладнання та витонченої алгоритмічної мови. Виходячи з цього, існує чітка необхідність кращої обізнаності розробників автоматизованих комп'ютерних систем із концепцією прогнозуючого технічного обслуговування.

В статті описано суть концепції прогнозуючого технічного обслуговування, її фундаментальні підходи, а також основні фізичні процеси, на яких базуються процедури прогнозуючого технічного обслуговування: (1) чіткі компоненти частотної вібрації, що властиві всім типовим видам поломок; та (2) постійна амплітуда кожного окремого компонента вібрації. Підкреслено важливість обізнаності із даною концепцією для розробників автоматизованих комп'ютерних систем. Також в статті окреслено найбільш проблемні площини застосування комп'ютерних систем для прогнозуючого технічного обслуговування, а саме розвиток ефективних комп'ютеризованих систем для збору та аналізу величезних масивів даних (обробка великих даних), та розвиток систем, що підтримують інтелектуальні з'єднання розумних пристроїв за допомогою інтернет-протоколів (інтернет речей).

***Ключові слова*: прогнозування, компоненти частоти вібрації, механічне обладнання, швидке перетворення Фур'є, обробка сигналу, великі дані, інтернет речей.**