System monitoring and maintenance policies: a review

Giuseppe Curcurú[1], Marco Cocconcelli[2], Riccardo Rubini[2] and Giacomo Maria Galante[3]

[1] Istituto Euro MEditerraneo di Scienza e Tecnologia
Via Michele Miraglia, 20, Palermo, Italy
{giuseppe.curcuru}@unipa.it
[2]University of Modena and Reggio Emilia
Via Amendola 2 - Pad. Morselli, 42122 Reggio Emilia, Italy
{marco.cocconcelli, riccardo.rubini}@unimore.it
[3]University of Palermo
Viale delle Scienze 1, 90128 Palermo, Italy
{giacomomaria.galante}@unipa.it

Abstract

In the industrial context, the main goal of the maintenance team is to avoid sudden failures that can cause the stoppage of the system with a consequent loss of production. This means that each maintenance action must be performed before the degradation level of a system exceeds a critical threshold beyond which the failure probability becomes high. The increasing importance given to maintenance is shown not only by the great deal of literature on the topic, but also by the interest in transforming this area from a managerial area to a branch of applied mathematics (Operational Research or Statistics). Maintenance is now considered as a subject and much research activity is concerned with its mathematical modeling rather than with the management processes relating to maintenance itself. In [1], Scarf evidences the great importance of the mathematical modeling of maintenance and the correlated strategic support given by the maintenance management information systems. Nevertheless, no model can be built without an exhaustive collection of data. By data, Author means not only specific figures regarding, for example, failure times, but all information related to the process under study. With the recent advent of condition monitoring and the development of appropriate decision models, critical components of a system can be tracked through appropriate variable(s) correlated to their degradation process, logistic support (for example, spares inventory) can be provided, maintenance history can be stored, predetermined maintenance activity can be alarmed and management reports can be produced. The use of condition monitoring techniques reduces the uncertainty operators feel about the current state of the plant. For example, knowledge about the vibration levels of a rotating bearing gives engineers confidence about its operation in the short term. Data acquired by monitoring systems, maintenance histories collected for specific components can be considered fundamental resources for the mathematical modeling of the maintenance activities. This paper is the first part of two [2], presenting the transition from preventive maintenance policy to the predictive one. In particular, the paper presents a brief review of the subject and some critical considerations about the two maintenance policies.

1 Generalities on maintenance policy

When dealing with maintenance theory, it is necessary to specify the terminology, structure and objectives of different maintenance policies. Generally, maintenance is classified in three different ways: corrective maintenance, preventive and predictive maintenance. Therefore, a brief presentation of these different approaches will be presented.

1.1 Corrective maintenance

Known with other terms as run-to-failure (RTF), reactive maintenance or breakdown maintenance, corrective maintenance adopts a simple philosophy: maintenance action is performed only when a failure happens.

Therefore, it is a reactive maintenance [3]. Generally, a reactive maintenance philosophy is not too much adequate to the industrial needs. Actually, the maintenance staff tries to avoid sudden failures that can cause the stoppage of the production system and affect costs. The implementation of more sophisticated maintenance approaches in the last decades is becoming a must.

1.2 Preventive maintenance

In order to reduce the probability of failure that can cause the stoppage of a production system, preventive maintenance (PM) policy adopts the opposite philosophy: maintenance action must be performed before system fails [4]. This philosophy is based on the simple consideration that every machine/system will fail with time and use because it ages with time and use. The European standard (EN 13306, 1998) defines PM as maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item. It can be generalized as all actions that should be taken on the machine in order to minimize the occurrence of unexpected downtime [5]. PM is a predetermined policy. Maintenance actions are performed at regular time intervals fixed on the basis of statistical considerations by considering lifetime distributions of the items, generally based on assumptions or experiments that involve the population which a component/item belongs to. For instance, preventive maintenance can be scheduled according to mean time to failure (MTTF) or the bathtub curve [3]. PM policy can be not convenient from an economic point of view, because maintenance activities are scheduled without any consideration of the actual degradation path of each item/system. Actually, each component belonging to the same population can exhibit a different degradation behavior due to unavoidable physical differences and especially to different working and environmental conditions. Generally, the time t_p between two subsequent maintenance actions can be fixed in order to minimize the cost per unit of time and the total expected cost expressed by following mathematical formulation: $C(t_p) = C_p R(t_p) + C_f[1 - R(t_p)]$, where $R(t_p)$ is the reliability of the component at time t_p, estimated on the basis of the lifetime distribution of the population which belongs to, and C_f and C_p are respectively the cost paid for a sudden failure before t_p and the cost paid for a regular preventive maintenance action.

1.3 Predictive maintenance

Over the past decades, with the increasing of smart sensors and advanced electronic equipment, the implementation of different maintenance approaches has become more popular. Machines typically show signs of impending failures before their occurrence. Therefore, by monitoring, it is possible to know exactly the actual status of an item. For example, vibration analysis can provide early warning indications and then help to detect these failure mechanisms before they can reach an alarming level and cause the stoppage of the system. When time waveforms and frequency spectra are available, sophisticated statistical methodologies can be applied in order to draw information to be used as maintenance decision supports. Nevertheless, predictive maintenance policy is more than just a condition monitoring [6, 7]. Actually, it involves changes in maintenance decisions and management procedures. Maintenance activities are really triggered by the real maintenance needs without any considerations of the manager's scheduled activities. Since a predictive maintenance action is not carried out only in case of necessity, staff managers have more time [8] to plan the maintenance and repair activities. Therefore, the system stoppage can be planned in advance increasing system availability. Even the stocks of spare parts can become smaller. Then, reducing of the maintenance costs, of the unexpected failures and of the inventory of spare parts are the most relevant and visible benefits associated with the implementation of a predictive maintenance policy. However, it requires expensive equipment (sensors, electronic devices and so on) and high-trained personnel for measurements and for the analysis and implementations of results.

2 Condition monitoring and predictive maintenance

The EN-13306 (2010) defines condition monitoring (CM) as *any activity or set of activities, performed either manually or automatically, intended to measure at predetermined intervals the characteristics and parameters of the actual state of an item*. Therefore, condition monitoring informs about the functional status of items and makes possible an intervention before equipment breakdown. Condition Monitoring (CM) received a great deal of attention in literature [9, 10].

In this context, Condition Based Maintenance (CBM) represents one of the main application areas of condition monitoring. Actually, system operating conditions are defined through a non-invasive data collection that can be performed in two ways:

1. continuously on the platform through installed transducers and sensors
2. periodically at the platform with portable data acquisition systems with transducers and sensors.

By these collected measurements, the current condition can be appreciated, but mostly defects can be detected (*diagnostic phase*) and the future condition (*prediction phase*) estimated. Then, the remaining useful life (*prognostic phase*) can be determined [11, 12, 13]. Then CBM becomes the driver for system maintenance and the collected information can be used by the maintenance decision-maker to maximize the system availability or to minimize the expected costs [1]. This proactive approach can result more efficient than the systematic preventive maintenance policies that are exclusively based on the a priori statistical knowledge of the system/component lifetime [14]. However, for its implementation, more skills and complex considerations are needed.

Actually, to implement the prognostic phase, it is necessary to model system deterioration processes. The latter is a main assumption of CBM policy that involves statistical modeling with respect of the different causes that can determine a system failure [11, 13, 15]. For example, gamma processes can be adopted to model continuous or gradual deterioration processes due to wear in systems subjected to erosion [16]. To describe the usual characteristics of tool life and the tool cumulative wear process, the Bernstein probability density function (BDF) is suggested in [17]. For pipeline corrosion, the popular and conservative linear corrosion growth models is substituted by a novel polynomial chaos corrosion growth model constructed from extensive field data. Expected numbers of failures, repairs and replacements are evaluated by a probabilistic analysis using Latin hypercube sampling [18]. In [19] relevant degradation models are proposed. In particular, in [20, 21] hazard rate processes are presented while in [22] proportional hazards models are used to estimate thin-oxide reliability. However, their application in CBM context is not yet so spread.

Modeling the system failure mechanism is not a simple task. Different variables and stresses determine the system failure. Therefore, reducing the failure mechanism to one deterioration process is extremely poor. It is easy to understand that in a condition based maintenance frame, if the modeling process is too simplified, the resulting prognostic phase can be realistically far from the actual degradation process. More complex is the treatment of systems with more than one mechanisms of failure. In [23], a predictive maintenance policy for a continuously deteriorating system subject to stress is presented. Two failure mechanisms due to an excessive deterioration level and a shock are considered. Maintenance policy is optimized by combining Statistical Process Control (SPC) and Condition-Based Maintenance (CBM). The first is used to monitor the stress covariate, the latter to inspect and replace the system according to the observed deterioration level. A mathematical model for the maintained system cost is derived in order to assess the performance of the proposed maintenance policy and to minimize the long-run expected maintenance cost per unit of time.

Predicting remaining useful life is an important goal for multi-component systems. A significant interest is devoted to the optimal planning of maintenance for multi-component systems based on prognostic/predictive information when different component dependencies (economic, structural, stochastic) are considered. A dynamic predictive policy [24] is proposed for such a system by minimizing the long-term mean cost per unit time. Maintenance schedule is updated when new information on degradation and remaining useful life of components become available.

CBM does not act on system/item reliability. By measuring parameters representing the actual state of the item, it can only identify failures before they occur without any knowledge about their possible causes. In the sixties, a new maintenance philosophy was introduced: Reliability Centered Maintenance (RCM) [25]. Through Failure Modes, Effects and Criticality Analysis (FMECA), RCM can establish the maintenance needs to overcome failure or degradation tendencies of the involved items. Then, it is a systematic approach based on the assumption that every machine has a limited useful life and will eventually degrade to a failed state. For carrying out such a kind of maintenance methodology, one needs to identify and select the critical items in a system, to perform a risk analysis and then to produce a maintenance plan by identifying the maintenance intervals. In [26], a RCM policy is proposed for continuously monitored systems subject to degradation due to the imperfect maintenance.

All the maintenance policies try to increase system availability/reliability and reducing costs. In fact, minimizing the cost function is generally the proposed strategy to determine the maintenance intervals in whatever maintenance frame. To this purpose, replacing a reactive repair-focused maintenance policy with a proactive reliability-focused culture is becoming a common choice for the maintenance staff. Actually, maintenance improvements should be observable and measurable in terms of *efficiency* -less time- in terms of *effectiveness* -improvement of equipment performance and reliability-Performance indicators for the measurements of efficacy and efficiency are suggested in [27].

3 Bayesian approach in predictive policy

One of the most promising crossover between statistics and machine diagnostics is given by the application of the Bayesian inference to the condition monitoring [28, 29]. The Bayesian inference method is based on the Bayes' theorem [30], which is used to update the probability for a hypothesis as more evidence or information becomes available. In a maintenance context, items belonging to the same population can be theoretically characterized by a common mean drift expressing the population degradation pattern. However, unavoidable structural differences among components and different environmental and operating conditions can generate a different aging. By updating the a-priori information, common to all the items, through data coming from the monitoring system, it is possible to catch such differences and that was a common variable becomes a specific pattern of each single item. In [15], a stochastic model is adopted to describe the degradation process when an imperfect monitoring system is hypothesized. Through a Bayesian updating procedure, the convenience in adopting a predictive maintenance policy compared to the classical preventive frame is explored by simulations. In [31], Authors investigate how the use of a Bayesian updating procedure changes the characteristics of the failure rate associated with the time-to-failure distribution. In particular, while many classic age replacement policies rely on the assumption that the time-to-failure distribution has an increasing failure rate, it is demonstrated that the exponential time-to-failure distribution has a decreasing failure rate when a Bayesian updating procedure is adopted. Prediction of the remaining useful life (RUL) is a critical task for the implementation of a predictive maintenance policy. Since RUL can differ for similar components operating under the same conditions, in [32] a Bayesian approach is proposed for predicting the RUL of critical components. In recent works, Bayesian approach has been extended to other research areas. As an example, in [33], a Bayesian approach is proposed to manage a water distribution network- mainly constituted of pipes and valves- based on the evaluation of the network components reliability. Actually, Dynamic Bayesian networks (DBN) are used to assess the valves reliability as function of time. This dynamic approach allows the management of water distribution based on water availability assessment in different segments. To characterize the degradation process of rotational bearings, in [34] a Bayesian framework is proposed to integrate historical data with up-to-date *in situ* observations of new working units to improve the degradation modeling and prediction.

4 Conclusions

This paper proposes a brief review of the maintenance policies when a monitoring system is employed. After the review of the main approaches to maintenance, the paper focuses the predictive policy and the use of a Bayesian updating procedure in different fields.

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