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Intelligent integrated maintenance of manufacturing systems

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1. Introduction

The management of maintenance activities extremely affects the useful life of the equipments, product quality, direct costs of maintenance and consequently production costs. Thus, a reliable maintenance system is critical to maintain an acceptable level of profit and competition. Studies over 20 years have indicated that around Europe the direct cost of maintenance is four to eight percent of total sales turnover (Muller 2007). The indirect cost of maintenance is likely to be a similar amount. Thus, the potential savings from modern maintenance would be massive. Neural Management Maintenance System (NMMS) is a new technique yet to be further developed to reduce the involvement of analysts/engineers in data processing and thus adding quality in decision-making process. NMMS is based on Artificial Neural Networks (ANNs). The attractiveness of ANNs comes from their remarkable information processing characteristics mainly to nonlinearity, high parallelism, fault and noise tolerance, and learning and generalization capabilities. They have the ability to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been assigned to analyze. The NMMS would permanently monitor the system and suggest the most appropriate actions and strategies. This chapter explains a NMMS that integrates Corrective Maintenance (CM), adaptive Preventive Maintenance (PM) and Condition Based Maintenance (CBM) with suitable maintenance strategy addressed for each component/subsystem. The NMMS monitors the system and suggests the most appropriate maintenance actions. The main characteristics of the system includes; integration of expert opinion in a knowledge base, storing maintenance history and tracking components, alarming predetermined maintenance activities, alerting for spare parts and materials, updating schedules, considering limitation of resources, and measuring the effectiveness of the maintenance system. The easiness and intelligence of the proposed NMMS depends on keeping the maintenance data in MS-EXCEL spreadsheets and linking it to MATLAB® which in turn updates the models and makes the decisions.

2. Background

2.1 Maintenance Integration

Integration of maintenance into manufacturing organization is partitioned into "hard integration" and "soft integration" variables. The "hard" issues deal with integration supported by technology and computers. "Soft" integration, on the other hand, deals with human and work organizational integration issues. The two integration variables are closely related to the prevention variable, and are considered important enablers for effective realization of preventive policies (Jonsson, 2000). Integration must facilitate the bi-directional flow of data and information into the decision-making and planning process at all levels. This reaches from business systems right down to sensor level.

Hard maintenance integration issues deal with CMMS (Computerised Maintenance Management System) of the maintenance, repair and operating supplies store and scheduling of maintenance work, condition monitoring technologies, built-in test equipment, databases with reliability data on electronic and mechanical components, and decision support. On the other hand, soft integration issues of maintenance deal with the structure and the actors in the organization. New technology allows plants to have fewer humans directly participating in the physical manufacturing processes.

To integrate maintenance policies and study their impact on complex production systems, a powerful modelling tool is essential. One (or more) maintenance policies may be associated with each machine. Thus, an elementary cell is defined as a set made up of a machine, including associated maintenance policies, as well as its input/output stocks (Abazi and Sassine, 2001).

Maintenance Integration is necessary to increase availability and reliability of manufacturing systems to reduce unnecessary investment in maintenance without great increasing of investment. The integration is achieved through combining optimal maintenance types to have the benefits and to avoid the shortage of individual maintenance types. Thus, the proper maintenance program must define different maintenance plans for different machines.

The literature survey of the previous works indicates that a major interest of researchers has been the maintenance optimization not causing a measurable response from the engineering world due to two reasons:

1) *Applicability*: The works were mostly very theoretical, used difficult mathematics impractical to apply and required data were not then generally available.
2) *Accessibility*: The papers were published in journals of applied mathematics and operations research (OR), which most maintenance engineers do not read and few would understand if they did.

Thus, maintenance methods applied at present should be combined together within a comprehensive management maintenance system, which would permanently monitor the system and suggest the most appropriate actions. Thus, the scheme proposed herein serves this purpose, i. e. it combines maintenance integration and neural management maintenance system.

2.2 Artificial Neural Networks (ANNs)

ANNs are applicable to multivariable systems; they naturally process many inputs and produce many outputs. They are used as a black-box approach (no prior knowledge about a system) and implemented on compact processors for space and power constrained applications (Magali et al, 2003). ANNs; have ability to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" that can then be used to provide projections given new situations of interest and answer "what if" questions. ANNs learn by example and cannot be programmed to perform a specific task. The examples must be selected carefully otherwise the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

The initial weights of an ANN play a significant role in the convergence of the training method. Without a priori information about the final weights, it is a common practice to initialize all weights randomly with small absolute values. In linear vector quantization and derived techniques it is usually required to renormalize the weights at every training epoch. A critical parameter is the speed of convergence, which is determined by the learning coefficient. In general, it is desirable to have fast learning, but not so fast as to cause instability of learning iterations. Starting with a large learning coefficient and reducing it as the learning process precedes results in both fast learning and stable iterations.

2.3 Types and applications of ANNs

There are different types of ANNs according to how data is processed through the network. Some of the more popular ANNs include multilayer Perceptron (MLP), learning vector quantization, radial basis function (RBF), Hopfield and Kohonen networks. Some ANN are classified as *feed forward* while others are *recurrent* (i.e. implement feedback) depending on the direction of data flow. Another way of classifying ANNs is by their learning method, as some ANN employ supervised training, while others are referred to as unsupervised or self-organizing.

Magali et al. (2003) presented a comprehensive review of the industrial applications of ANNs in 12 years prior to 2003. The study found that the approximate percentage of network utilization was: MLP, 81.2%; Hopfield, 5.4%; Kohonen, 8.3%; and the others, 5.1%.

2.4 Modelling of maintenance systems

A manufacturing system of one failure mode can have one of two transition states either in operation mode or in failure mode. Figure 1 shows the transition diagram of a system that can either be in up (operating) or down (failed) state. A good maintenance management system is to decrease the failure rate and increase the repair rate.

In practical maintenance application, the measured variables and/or checked attributes are used to determine the next estimated time for replacement, repair or checking of the system. The steps for maintenance decision making are shown in Figure 2. Figure 3 shows more details of these steps and fine tools that can be used; it illustrates the system of data flow from the input phase to the output phase.
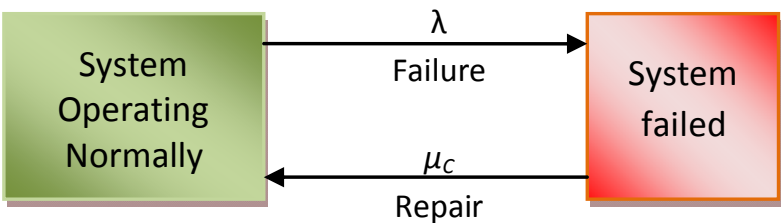
Fig. 1. System operating states

Fig. 2. Steps of maintenance decision

Fig. 3. Data flow from the input phase to the output phase

3. Design of the NMMS

3.1 Conceptual design of the NMMS

NMMS should model the manufacturing system in all its details, process the data and take the maintenance decisions. The system is designed to integrate maintenance in the manufacturing system and contribute to achieve high performance. It eases the bi-directional flow of data and information into the decision-making and planning process at all levels. Figure 4 shows the system of the maintenance optimization process in NMMS and Figure 5 explain the learning mechanism of the ANN-based system.

Fig. 4. The maintenance optimization process