Paper:

Intelligent Hybrid System: A Reliability-Based Failure Management Application

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[Received November 22, 2001; accepted December 3, 2001]

Abstract The integration of different intelligent techniques (such as Artificial Neural Networks, Fuzzy Logic, Genetic Algorithms, etc.) into a hybrid architecture allows to overcome their individual limitations. In industrial environments, these intelligent techniques can be combined to reach more effective solutions to complex problems. On the other hand, failure management in processes, equipment or plants, acquires more importance in modern industry every day, in order to minimize unexpected faults and guaranties a greater reliability, safety, disposition and productivity in the industry. In this paper, an intelligent system is designed for failure management based on Reliability Centered Maintenance methodology, Fuzzy Logic and Neural Networks. The system proposes the maintenance tasks according to the historical data of the equipment.

Keywords: intelligent hybrid systems, neural networks, fuzzy logic, maintenance, failure management, reliability-centered maintenance, industrial automation

1. Introduction

The intelligent techniques such as Artificial Neural Networks (ANNs), Fuzzy Logic (FL), Genetic Algorithms (GAs), etc., have been developed in order to solve problems from imprecise and quantitative data. FL is conceptually easy to understand, it is flexible, tolerates inexact data, it can be mixed with other techniques and it is based on natural language.[1] An ANN is a model designed to emulate some of the computing capacities of the human brain. This type of model includes both functional characteristics as topological configurations of the brain. The most important characteristic of the ANN is its learning capacity, defined by the adjustment of their interconnection weights.[2] The application areas where these techniques have been used are the following: processes control, pattern recognition, fault detection and diagnosis, etc.

However, what makes humans be successful in dynamic and complex environments is the combination of different types of knowledge sources. The emulation of the human capacity to solve problems from hybrid knowledge sources has been researched at recent years. In this way, Intelligent Hybrid Systems (IHS) based on intelligent techniques have been proposed.[3] These systems integrate the different intelligent techniques (Artificial Neural Networks (NN), Fuzzy Logic (FL), Genetic Algorithms (GA), etc.) in order to solve complex problems. Intelligent techniques have been extensively used in industrial problems. On fault detection and isolation tasks, the model-based approaches have been successfully used (observers and filters design, etc),[4] but also, approaches using artificial and computational intelligence have been extensively applied reaching interesting results.[5] IHS in other industrial tasks have been also reported.[6] However, the systems development oriented to failure management at large scale process maintenance is a complex problem in industrial environments which needs special attention. Some industries neglect to do proactive measures oriented to fault prevention and diagnosis only just applying corrective measures. In order to solve this problem, many methods, as the Reliability-Centered Maintenance (RCM) methodology oriented to the preventive maintenance, have been developed.[7,8] Maintenance is a key piece in the business strategy, which not only ensures the equipment and system life, but also the continuous flow of the productive process and the quality of the results. In this paper, we propose an IHS

Fig. 1. Failure pattern type A.

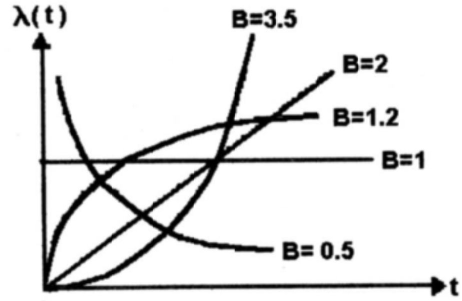

Fig. 2. Typical curves of λ(t).

for failure management based on the RCM principles. This system has been designed in a modular form allowing the use of different intelligent and conventional techniques into each module, in order to propose the adequate maintenance tasks from the historical data of the equipment failures.

2. Theoretical Basis

In this section we present basic ideas on reliability-based failure management.

First, we introduce some basic aspects about failure management, such as the definition of reliability curves and the Weibull's law. Then, some aspects about the RCM methodology are presented.

2.1. Reliability-centered Maintenance

A failure or breakdown is the inability of a system or element to fulfill its mission. Reliability is defined as the possibility of an equipment or component do not fail while it is working, for a determined period of time, when it is operated under reasonable conditions. The equipment failures are due to wrong operation or bad maintenance. In most cases, the replacement of a defective part does not mean the elimination of the failure causes, originating new equipment stopping. For this reason, it is fundamental to know the relations between the failures, symptoms (failure modes) and causes. The RCM methodology develops strategies based on the understanding of the equipment functions and failure modes, to determine maintenance requirements in its operative context, proposing maintenance tasks which are technically and economically possible. The RCM methodology has two principal categories of preventive tasks, which are On-Condition tasks and On-Time tasks[7,8]:

- ***On-Time tasks***: they imply repairing or replacing the equipment before the specified limit-age.
- ***On-Condition tasks***: they involve monitoring the physical conditions of the equipment, which allow to give a warning about the possible equipment failure (potential failures).

These tasks allow preventing real failures, avoiding their consequences. The reliability curves (or failure pattern) are a key element on the RCM methodology. If we know the failure pattern associated to a given equipment, then a particular preventive task can be considered for such equipment.

2.2. Reliability Curves

If enough information can be gathered to define the time distribution of failure occurrence for a particular equipment, then we can define a failure density function, also called Reliability Curve, for such equipment. This function allows to know the failure rate λ(t).[9,10] Certain typical reliability curves (or failure pattern) are used to describe the equipment reliability. They are classified as A, B, C, D, E and F type according to the qualitative behavior of λ(t). The behaviour of such patterns is well known; for example, the failure pattern type A is shown into the **Fig.1.**

We can observe on the **Fig.1** that the useful life of the equipment has three defined periods according to the behaviour of the failure rate. These ones are:

- *Starting period*: The failures occur during the first times after turn on the equipment. This period is also known as "child morbidity".
- *Normal operation period*: The failures are randomly produced from uncontrollable external agents.
- *Wear out period*: In this period, the failures depend on the time and they are caused by the system or equipment age.

2.3. Weibull's Distribution

The mathematical expression that describes the failure rate λ(t) for an equipment defines its theoretical life model. Particularly, the Weibull's life model is widely used, allowing to obtain decreasing, constant or increasing failure rates. According to the Weibull's law, the failure rate function is defined by the Eq.(1) [9,10]:

$$\lambda(t) = \frac{B}{V}\left(\frac{t}{V}\right)^{B-1} \quad \ldots\ldots\ldots\ldots\ldots (1)$$

where:

V = parameter of life characteristic; B= shape parameter.

In **Fig. 2**, typical qualitative behaviour of the failure rate function for some values of parameter B, are shown (with V=1). Based on the historical data about the failure