Intelligent Hybrid System: A Reliability Based Failure Control Application

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Abstract: - Failure management in processes, equipment or plants acquire more importance in modern industry every day, as it allows us to minimize unexpected failure risk and guaranties a greater reliability, safety, disposition and productivity in industry. On the other hand, the integration of different intelligent techniques (such as Artificials Neural Networks, Fuzzy Logic, Genetic Algorithms, etc.) in a hybrid architecture allows us to overcome individual limitations in those techniques. In this paper, an intelligent model is designed for failure management based on Reliability Centered Maintenance methodology, Fuzzy Logic and Neural Networks. The system allows us to generate adequate maintenance tasks according to the historical data of the equipment involved.

Key Words: - Equipment Maintenance, Failure Management, Reliability Centered Maintenance, Industrial Automatization, Neural Netwoks, Fuzzy Logic, Intelligent Systems. CSCC'99 Proceedings, Pages:5231-5239

1 Introduction

Today, it is common to find industries which adopt recesive measures oriented to damaged equipment restauration, abandoning proactive methods oriented to failure prevention and diagnosis as primary activities [1]. This occurs due to the lack of understanding as to how the equipment works, and consequently, as to why the equipment fails. Tending to the maintenance area need of introducing proactive methods which ensure a greater disposition of the plant, Reliability Centered Maintenance (RCM) methodology has risen [1]. This methodology develops structures oriented to the optimization of prevention maintenance task use.

On the other hand, in recent years, a great number of hybrid systems based on intelligent techniques, as decision backups and control processes have been produced, among others [2]. This systems combine different intelligent models (Artificial Neural Networks (NN), Fuzzy Logic (FL), Genetic Algorithms (GA), etc.) to solve problems. This integration points to overcoming limitations in each tecnique, through several combination or fusing mechanisms.

In this paper, we propose an Intelligent Hybrid System (IHS) for failure management, designed by modules to allow for the use of different intelligent and statistic techniques, to generate adequate maintenance tasks according to the historical data of the equipment involved in the system.

2 Theoretical Basis

In this section we present some fundamental aspects about failure management, such as the basic reliability concepts and the Weibull law, to obtain reliability curves. Later, some aspects about RCM methodology are presented. Finally, basic ideas on intelligent techniques to be used are addressed.

2.1 Failure Management

In most cases, equipment failure are due to inadequate forms of operation or to a bad maintenance. Replacement of a defective part does not mean, at all, eliminating the failure cause. If in any system we pay little attention to failure symptoms and causes, these will repeat, originating new equipment stopping and more expenses. For this reason, it is fundamental to stablish relations among failures, symptoms and causes.

In all failure definitions reference is made to two fundamental concepts which are system or element working capacity, and the function for which it was designed. Thus, we will consider a failure or breakdown as the inability of a system or element to fulfill its given mission when designed. This definition involves both serious as well as simple failures, also called catastrophic and partial, respectively.

2.1.1 Reliability Curves

Reliability is defined as the possibility of an equipment or component not to fail while it is working, for a determined period of time, when operated under reasonable uniform conditions [3].

If enough information can be gathered to define time distribution of failure ocurrence for a particular group of equipment, then we can define a failure density function, also called Reliability Curve, for such equipment type. This function allows allows us to know instant failure rate, called λ(t), this being the interest parameter in the reliability study. As failure rate is a time function, we can represent through a curve. Such a parameter indicates the failure number in equipment or component which are produced in a working instant *t* [4].

Certain typical curves are used to describe equipment reliability, which will be called failure patterns or reliability curves, and are classified as A, B, C, D, E and F type according to qualitative behaviour of λ(t). Such pattern characterization is well known [5], type A being the pattern that which gathers all possible failure patterns from an equipment (see figure 1).

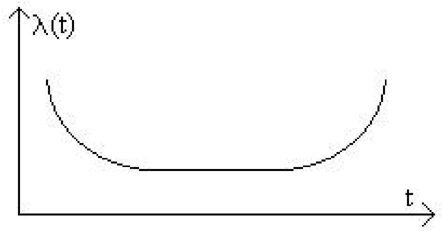

Fig. 1. Type A Failure Pattern

In the figure, we can observe that an equipment's useful life can present three defined periods which are a function of the failure rate behaviour. These are:

- *Start period:* Its important characteristic is that the failures present here are those which occur during the start, which are also known as "child morbility" (factory deffect failures).
- *Normal operation period:* Its most important characteristic is that failures that occur are aleatory and are caused by uncontrollable external agents.
- *Wear out period:* Its most important characteristic is that failures depend on the time and are caused by the system or equipment age.

2.1.2 Weibull Distribution

The element to determine an equipment reliability is failure frequency in time. If enough data can be gathered to define failure ocurrence in time distribution for an equipment, then failure rate function can be determined [6]. If failure rate is gotten as a time function, a curve is generated called Reliability Curve or Failure Pattern. The importance of this curve lies in its use to adequately select preventive maintenance tasks to be applied [5].

Mathematical expression which describes rate failure for an equipment life period constitutes its theoretical life model. Weibull's life model is characterized by its modulation flexibility, that allows its adaptation to any life period. Particularly, using Weibull's distribution decreasing failure rates can be obtained, constant or increasing; allowing for the description of all failure patterns, except failure pattern type A, which is constituted by three life periods (start period, normal operation period, and wear out period).

Failure rate function, according to Weibull's law, is defined by the equation (1) (for more detail see [4]):

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

where:
V= scale parameter or characteristic life,
B= shape parameter.

In figure 2, typical curves of the failure rate function for some B values are shown (V=1).

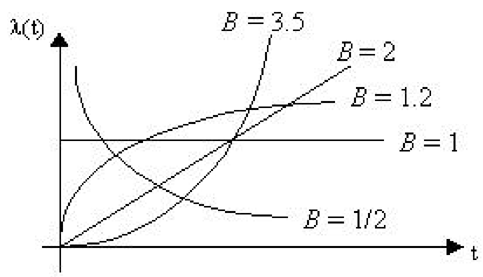

Fig. 2. Typical curves of Failure Rate Function

Weibull's parameter obtention, is based in the knowledge of a series of failures which occur in a system or equipment (historical data about failure ocurrence), calculating time between failures (TEFn), which will be ordered from oldest to most recent (from n=1,...N). Then for each TEFn failure probability will be calculated PF(N) and survival probability PS(N), defined by equations (2) and (3), respectively [6].

$$\mathrm{PF(n)} = \frac{\mathrm{n}}{\mathrm{N+1}} \quad (2)$$

$$\mathrm{PS(n)} = 1 - \mathrm{PF(n)} \quad (3)$$

where:
N: is the number that identifies the longest time between failures.

Theoretical estimation Weibull distribution parameters (V and B) is obtained by survival function by the method of the square minimums. So, these parameters are defined by equations (4) and (5).

$$V = e^{\left[\frac{\sum_n Z_n b_n - \sum_n Z_n \sum_n b_n}{\sum_n Z_n b_n \sum_n b_n - \sum_n Z_n \sum_n {b_n}^2}\right]} \tag{4}$$

$$B = \frac{\Sigma Z_i b_i}{\Sigma b_i - Ln(V)\Sigma {b_i}^2} \tag{5}$$

where:
b_n=1/Ln(TEF_n)
Z_n=A/B
A=Ln(Ln(1/y_n))
B=Ln(TEF_n)
y_n=PS(n)

Another important function is the failure probability distribution F(t), or also called unreliability, which is an equipment probability of not working for a determined period of time, under normal operating conditions. This possibility, according to Weibull's law it is defined by equation (6).

$$F(t) = 1 - e^{-\left(\frac{t}{V}\right)^B} \tag{6}$$

Failure probability is of great importance since this probability tends to 1 failure rate will be indicating maximum failure number an equipment can present before it stops working. In such a sense, failure rate meaning is going to be given by failure probability which is had for that instant in time.

2.2 Reliability Centered Maintenance (RCM)

Maintenance is a key piece in bussiness strategy, which not only ensures equipment and system life, but also the continuous flow of productive process and the quality of the result. RCM methodology develops strategies based on the basic principal of understanding equipment functions and failure modes, to determine maintenance requirements in its operative context, proposing task types which are technically and economically possible [5, 7].

Reliability (or failure) pattern determination is a key element in the RCM methodology and therefore it is necessary to know it [7]. Its importance is centered on the fact that if you know the failure pattern which can associated to an equipment, failure prevention measures can be taken on time for such equipment. Reliability criteria according to RCM has to principal categories of preventive tasks which are: condition tasks and time tasks [5, 7].

- On-Time tasks: these imply repairing or replacing an equipment before the specified limit age, regardless of such an equipment condition for the moment of task application.

- On-Condition tasks: These tasks involve monitoring the equipment's particular physical conditions, which tendencies warn about the possible appearance of an equipment failure (potential failures). The application of these type of tasks allows for actions to prevent real failures, avoiding their consequences.

2.3 Intelligent Techniques

The intelligent computer area involves a series of emerging techniques, such as artificial neural networks, genetic algorithms, fuzzy logic, expert systems, etc. In this section we make an introduction to intelligent techniques to be used.

2.3.1 Fuzzy Logic (FL)

This technique is fundamentally based on the fuzzy set theory proposed by Zadeh, in which elements can partially be members of a set [8]. Then, the membership rate of an element to a particular set can take several values between zero and one., where zero indicates complete exclusion and one is complete membership. Thus, in FL declarations such as "the temperature now is warm" pass through membership rate evaluation from a given temperature for the "warm" fuzzy set.

FL uses a group of operators similar to those used by boolean logic, that is, AND, OR, NOT. Eventhough, each of the operator's interpretation is different. If we suppose two fuzzy sets A and B, case A AND B=C assigns a given pointed value, the membership rate to set C, defined as the least of the membership rates of such a pointed value to fuzzy sets A and B. Similarly, case A OR B corresponds to the maximum membership rate between A and B for a given pointed value.

Given the elements of the fuzzy set and all fuzzy operators, we can make rulers "IF-THEN" in a form similar to boolean logic. Eventhough, in FL the specific conclusion for the THEN portion of a ruler is based on the truth rate of the IF portion.

FL use is widely promoted in complex situations, since it is conceptually easy to understand, it is flexible, tolerates inexact data, it can be mixed with other tecniques and it is based on natural language.

Among the areas of application were it has been used, we have: control, pattern recognition, etc.

2.3.2 Neural Networks (NN)

Neurons are nerve cells which constitute the primary elements of the central nerveous system. In general, neurons are capable of receiving signals which come from other neurons, process these signs, generate nerveous pulses and transmit them to other neurons through extensions called dendrites [9]. In the human brain, neurons are interconnected in complex spacial topologies to form the central nerveous system. Neural operation can be seen as a process where the cell executes a sum of signals which arrive through their dendrites. When this sum is larger than a certain threshold, the neuron responds transmiting a pulse through its axon. If the sum is smaller than the threshold, the neuron is not activated.

An artificial NN 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 in the brain neurons. Eventhough, what makes a NN powerful is the interconexion strength among its neurons, not the neurons themselves. Therefore, the most important characteristic of neural nets is learning capacity, defined as the adjustment of its interconexion pondering.

Neurons, as basic elements of net processing, are compossed by: a pondered entry adder, an activating function, and a training or learning ruler. All learning methods can be grouped in two categories: supervised learning methods and non-supervised learning methods [6]. Among the application areas, we have: control, pattern recognition, etc.

2.3.3 Intelligent Hybrid Systems (IHS)

Humans are beings who can process information from hybrid sources. Thus, knowledge used by humans is due to a genetical information combination and information acquired through learning. This combination of different types of knowledge sources has allowed humans to be succesful in dynamic and complex enviroments [2].

Human capacity emulation to process from hybrid knowledge sources, has been the object of much research. This has led to the use of different intelligent techniques, which have been developed independently, because such techniques have prduced encouraging results in particular tasks, but certain complex problems could not be solved independently. This is because each intelligent technique which make it suitable for certain particular problems and not for others.

IHS have come as intelligent technique integrating elements. They integrate skills from each technique to solve complex problems, not only combining different intelligent techniques, but also integrating such techniques to conventional systems (for example, as data base, etc.). There are different ways of integrating intelligent techniques: combining its skills, fusing a technique into the other (for example, fuzzy inference system using neural networks), or transforming certain parts of a technique for another (for example, learning process of a neural network made by a genetic algorithm).

3 Problem Formulation

In a previous paper [1,10], a failure management computer model based on RCM and on an intelligent technique called Fuzzy Classifier System. In this model knowledge of the equipment failure mode reliability curve was assumed. Such reliability curves are associated to the equipment failure pattern, which was not explicitely known in that paper. To obtain such reliability curve it is necessary to have the historical data of the equipment, which must store the times an equipment has stopped working for a particular cause [3, 4].

According to the RCM, preventing maintenance tasks proposition for a particular equipment is intimately attached to the failure pattern type such an equipment follows. In this paper an IHS will be developed which allows for adequate task proposal from failure patterns, using historical data of equipmqnt failure. Furthermore, only equipment failure behavior characteristics will be considered, constructing and analyzing its failure patterns to define technically possible maintenance tasks. Associated expenses to these tasks must be analyzed by another subsystem, which also contemplates consequences which could be failure generated (wit its expenses respectively), so as to determine which of the tasks proposed by IHS are economically possible [5] (see figure 3).

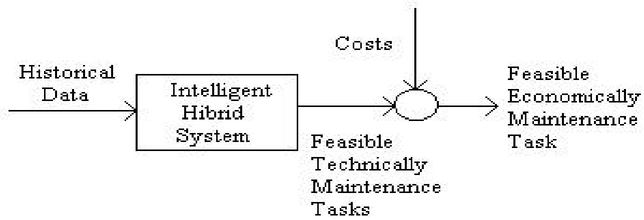

Fig. 3. Failure Management IHS in an Operational Enviroment

4 Failure Management IHS Design

In this section, failure management IHS modular design in industrial equipment is shown, which not only combines different intelligent techniques, but also conventional calculus systems. The first module is based on the formal method described in section 2.1.2, to obtain the Weibull parameters (V and B) which describe the reliability curve of the equipment. A NN is used in the second module to identify which failure pattern type is associated to the equipment as a function to A and B values. Finally, the last module is a fuzzy interference system which selects the most adequate type of maintenance task technically possible to apply to the equipment, according to pattern failure (see figure 4). Intelligent system outputs will be the maintenance tasks, and the inputs will be equipment failure times sampled directly from the particular plant, or provided by someone who knows the equipment (expert).

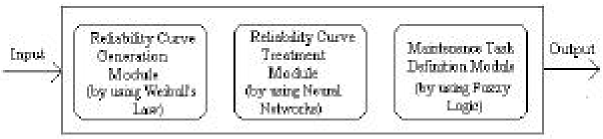

Fig. 4. IHS Modular Design for Failure Management.

Below, each of the modules which make up this design, detailing its behavior, pointing out its inputs and outputs, as well as interaction between them.

4.1 Reliability Curve Generation Module

This module allows to catch necessary information to obtain reliability curve or pattern, and its generation (see figure 5).

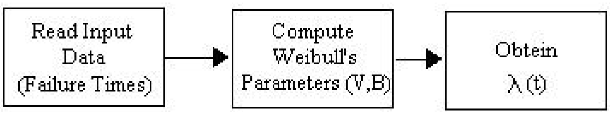

Fig. 5. Reliability Curve Generation Macroalgorithm

Input data to this module are the times in which the equipment has stopped working due to some failure (historical data). This data is processed by this module, based on the methodology shown in section 2.1.2, obtaining as an output, the Weibull parameter values (V and B), as well as $\lambda(t)$ for the equipments involved.

4.2 Reliability Curve Treatment Module

Parameter A and B combination to generate a particular failure pattern is not theoretically stablished (some criteria obey practical estimation [3,4,6,11]), it is necessary to make a check up of the generated curve by Weibull parameters to associate it to any known failure pattern (see section 2.1.1).

This module consists of a NN which allows to associate an equipment to value pairs V and B, to a known failure pattern. NN importance lies in associating, as accuretly as possible, the $\lambda(t)$ generated curve to a known failure pattern, because certain Weibull pair parameter values do not define to which pattern the curve belongs to, well. These values are those found in the rank limits to which each pattern is associated according to the V and B values which Weibull's distribution describes (see section 2.1.2).

The NN used is a multilayer perceptronic net trained according to a standard propagation algorithm (see figure 6) [9].

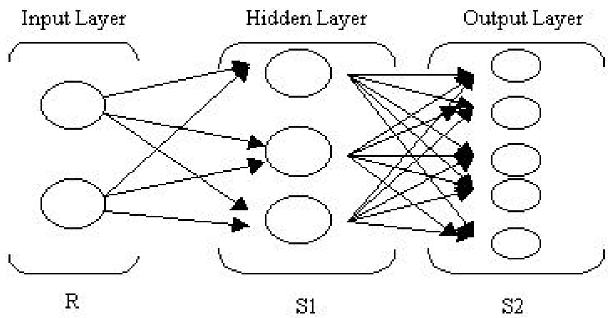

Fig. 6. NN Arquitecture

where:
R= 2 neurons on input layer.
S1=3 neurons on hidden layer.
S2=5 neurons on output layer.

The NN was trained so that the output neuron which represents the correct pattern has a 1, and in the rest of the output neurons has a 0. The number of intermidiate neurons was calculated in the net's tuning fase. This NN is trained for experimental data input-output value pairs at disposition, which involve different ranges of the values B and V, and the respective failure pattern they represent.

For it to work, the net receives an input the value pairs which are obtained in the first module (Weibull's parameters V and B). The NN output determines the failure pattern to which the equipment belongs, and this output will be the next module input (fuzzy interference system).

4.3 Maintenance Tasks Definition Module

This module consists of a HIS composed by a set of generic inference rules, some fuzzy other pointed. Such rules are based on RCM, to determine technically possible maintenance task applications, such as On-Time task (TT) or On-Condition task (CT) [5], so as to prevent failures in the equipment or in the system (see figure 7).

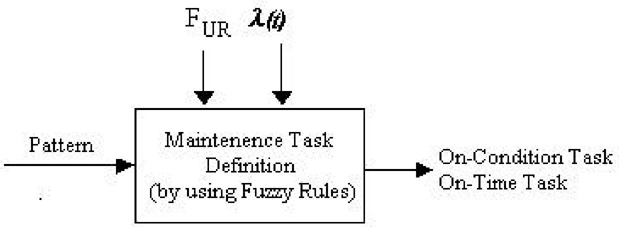

Fig. 7. Maintenance Task Definition Module Design

This module uses the reliability curve (pattern) type recognized in the previous module, as well as other inputs such as the λ(t) function (obtained in the first module), and the last equipment repair F*ur*, due to a time task application, which is provided by the persons in charge of equipment maintenance.

From the λ(t) the minimum, average and maximum failure number is calculated within that module an equipment can present in a determined period of time (x, y, z). This information is necessary to generate belonging function for the failure number fuzzy variable NF which represents the number of failures in an instant in time *t.* The date of the last repair F*ur* is needed to calculate the instant in time in which the operator wishes to know what action to take in the equipment, in a present instant in time $t_{present}$.

4.3.1 Module Fuzzy Characterization

Fuzzy variables defined in this module are:

Number of Failures (NF(t)): Represents the number of failures by time unit produced in an equipment. Their value is defined λ(t) for a given instant in time ($\lambda(t_{present})$). Fuzzy sets defined for this variable are *Low, Average, High.*

The membership function for this fuzzy variable is shown in figure 8. Discourse universe is [*0* number of failures, *z* number of failures] where *y* is the average number of failures and *z* is the maximum number of failures associated to the equipment.

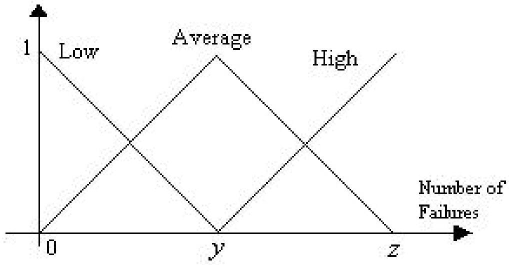

Fig. 8. Membership Function for Variable NF(t)

where:
y=z/2
$z=\lambda(t_{max})$; where t_{max} is the t value such that F(t)=p, where "p" is the maximum allowed probability ("p" is given by the user or expert).

Working On-Time task (RTT): Represents the urgency of applying a maintenance time task, according to NF value. Its value is defined according to what was proposed for RCM. Fuzzy sets defined by this variable are *Low, Average, High.*

Working On-Condition Task (RTC): Represents the urgency of applying a maintenance condition task, according to NF value. Its value is defined according to what was proposed by the RCM. Fuzzy sets defined for this variable are *Low, Average, High.*

Fuzzy variables *RTT, RTC* are characterized by the membership function shown in figure 9, with a universe of possibility discourse [*0, 1*] which represents the measuring scale to take an action in respect to the maintenance task about time.

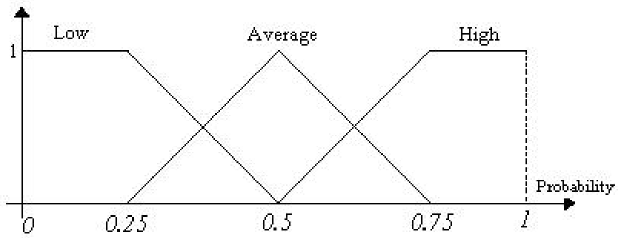

Fig. 9. Membership Function for *RRT and RTC* Variables

Other variables such as Pattern and OCT, are not fuzzy, they indicate a concrete value or action. Pattern represents the failure pattern type (A, B, C, D, E, F) and OCT indicates the concrete working On-Condition task.

4.3.2 Inference Engine

The generical inference engine which constitutes this module's heart, which uses the proposed procedure pattern for RCM, is as follows:

1. If *Pattern* is (D, E, or F) **then** OCT (Punctual Rule)
End If
2. If *Pattern* is (B or C) **then** *Determine NF ($t_{present}$)* (Punctual Rule)
If <*NF(t_{actual})*> **then** <RTT> or <RTC> (Fuzzy Rule)
End If
End If

The *Pattern* variable is not fuzzy, but works for the taking of the adequate decision as well as for the concrete action to apply On-Condition task (OCT) when the pattern is B or C. On the other hand, the variables which describe the maintenance task to work on (RTT and RTC) are fuzzy, as well as the variable which represents the number of failures for an instant in a determined instant in time (NF ($t_{present}$)), so as to estimate a task which should be applied based on the relationship pattern-failure.

To obtain present time “$t_{present}$” we must take into consideration the last repair date for the equipment, which is an external imput to the system. The time which has run since that last repair time to the instant in which the monitoring is being carried out (present time) is the one called “$t_{present}$” (see figure 10).

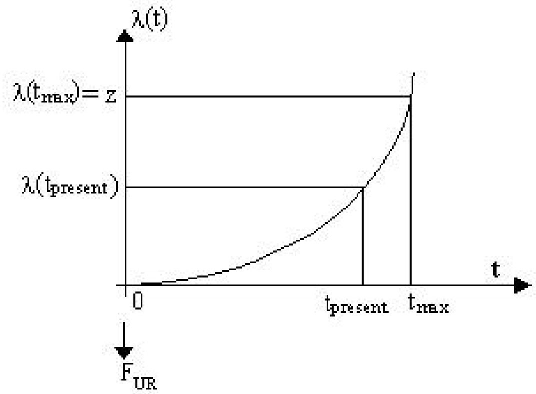

Fig. 10. Present Time Representation

4.4.3 Generical Fuzzy Rule Instances

Generical instances are based on the relationship given between NF and RTT or RTC. When the failure number are average or high, we should apply On-Time task,since the failures there increase in long term with time. On the other hand, when failures are low it is better to apply On-Condition task. Below we describe such relationships (instances) in respect to the generical fuzzy rule we have (see table 1):

If *<NF(t)>* **then** *<RTT or RTC>*

NF(t)			***RTT***			***RTC***		
L	A	H	L	A	H	L	A	H
X			**X**					**X**
	X				**X**		**X**	
		X			**X**	**X**		

Table 1. Generical Fuzzy Rule Instances

5 Application Example

Next an application example is presented which shows IHS at work. This system prototype was developed in MatLab® [8, 12].

Entry information to the system is the historical data on failure ocurrence in two different equipments (see table 2). You must be aware that in this case no information about which part of the equipment failed was registered for those given times. These data was generated in an aleatory manner, that is, it does not belong to any real practical case.

Failure time for equipment #1	**Failure time for equipment # 2**
590	1000
700	1920
800	2390
850	3001
900	3812
1987	5025
3567	5712
3723	5951
4563	6297
8076	6793
9887	6998
	7810
	8462
	8899
	9400

Table 2. Input Data to the Reliability Curve Generating Module

From these data, parameters which characterize Weibull distribution were workwed out (B and V) using the equations described in section 2.1.2 results are shown on table 2.

Equipment #1		Equipment #2	
B	*V*	*B*	*V*
0.6669	792.7518	2.0644	719.8793

Table 2. V and B values, obtained from Reliability Curve Generation Module.

Next, the module shows function λ(t) for each equipment, obtained through simulation (see figure 11). V and B values will be entry data to the second module, to be processed by the neural network and assign the equipments associated failure patterns. The results are shown in figure 11.

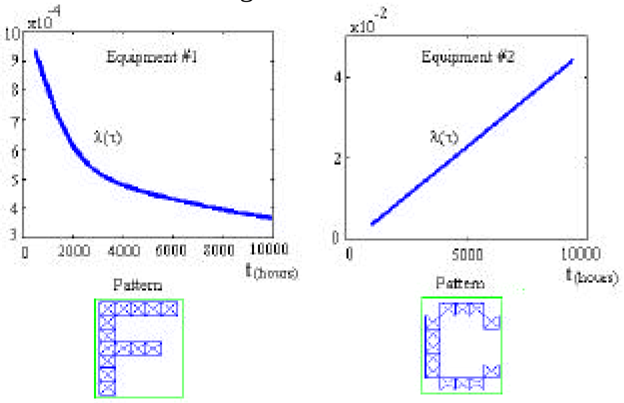

Fig. 11. Results Shown by the Reliability Curve Treatment Module.

Next, inputs to the third module are function λ(t) (obtained from the first module), the last repair time Fur (given by the user) and pattern type (recognized in the second module). From this information maintenance task to be applied for failure prevention in the equipents are determined.

This module also shows as an output the equipment's reliability curve showing the maximum time allowed t_{max} which you can wait before working On-Time task (time estimated in which the equipment will not fail). On this curve present time $t_{present}$ is also shown (time in which the equipment is being studied). This curve presentation will not allow the expert to miss life time left the equipment from present time.

Next results obtained for an equipment with certain V and B values are presented.

Input:

- B=2.608 and V=642.822
- Pattern=C
- Fur=1999 1 21 (year, month, day)

The determination module of maintenance tasks presents the output shown in figure 12.

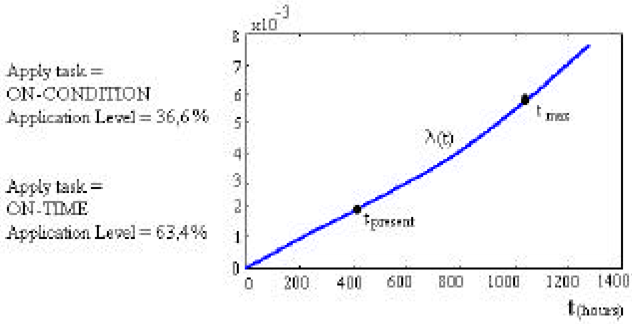

Fig. 12. IHS Output

The result presented by the system shows the state of an equipment or group of equipments for a determined moment $t_{present}$, indicating to the user the maintenance task type he must apply according to the reliability characteristics of the equipment and the time since the last repair. In this example, the system suggests working On-Time task with the most urgency (63%) which associates an On-Condition task (36%), eventhough, final decision is the operator's, guided by the present state of the equipment shown as an IHS output (see figure 12).

6 Conclusions

IHS for control and failure management in this paper, exhibits a great potential to solve the most important problems in the maintenance area, as are reliabilty curve estimation for equipments and adequate maintenance tasks proposed. Each IHS module uses the best tool to implement its function. Tests carried out on this system showed the neural network reaches a 90% failure pattern recognition rate.

Theoretical basis on which Weibull parameter generation module is based is such that, it allows IHS application not only for equipment reliability studies, but in plants. IHS integration into a more complex system allows to know the plant state and associate it to the equipments and their components. In this global application, IHS will estimate Weibull's parameters for the plant, for the equipments associated to it and for their components, having the equipments and their components historical data as an input. This way, IHS allows to have a global vision of the plant reliability and, in consequence, determine adequate maintenance tasks to prevent failures.

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