A methodology for quality control and evaluation in compressor assembly line.

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Abstract: This paper is concerned with the development of a methodology for quality control and evaluation in compressor assembly lines. The tools Artificial Neural Networks (ANNs), Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA) are used. Based on this approach, it is proposed the analysis of the main failure modes in compressor assembly lines and the automatic identification of these cases with neural networks. The objective is the reduction of the number of compressors not assembled within the company recommended technical standards. This proposal aims at the extraction of a feature of a primitive signal acquired by installed sensors in the measurement panel, and at the classification of the signs of perfect or defective compressors with a Neural Network. The obtained results are compared with the current system of measurement with the purpose of evaluating the proposal. The accuracy index of the proposed model is between 97% and 100% of correctly identified patterns.
Key-words: Methodology for quality control, Compressor Assembly Line, Artificial Neural Networks.

1. Introduction

The current situation of markets has stimulated companies to develop its products continuously, searching techniques for product improvement and cost reductions. In this process there is also the improvement of the product quality evaluation system, which was has been installed in the assembly line ending, preventing that product faults acquired during the assembly go to reach the consumer. The spare cost of reposition of each product may be hundreds of times its manufacturing cost. This requires a rigorous quality control in the assembly line. Even if these compressors have a satisfactory performance, vibration and noise have an important influence on the compressors quality evaluation. With the purpose of evaluating the compressors operations through proper subjective characteristics inherent to the human judgment, the use of artificial neural networks with the Failure Mode and Effects Analysis are considered together in this article. The objective of this analysis is developing a methodology for the segregation of defective compressors and identifying the main failure modes automatically, using for evaluation the spectra produced from compressors which are considered in fault. The fault patterns are associated to the defects that are found more frequently in the production line. A set of these faults was presented to a feedforward neural network for its training and validation. After this, the artificial neural network establishes criteria of automatic identification of faults in order to achieve a quality control of the produced compressors.

The intention of the present article is to work with FTA (Fault Tree Analysis) and FMEA (Failure Mode and Effects Analysis), allowing the information computed during the compressors assembly process indicate how the system can fail and which actions can be done, identifying the more efficient solutions in terms of cost (BILLINTON *et all*, 1987 and SAKURADA, 2001).

2. Relationship between the Fault Tree Analysis and Failure Modes and Efects Analysis

The FTA is a graphical tool that allows the identification of the failure path between a lower and a higher level of a system, Figure 1.

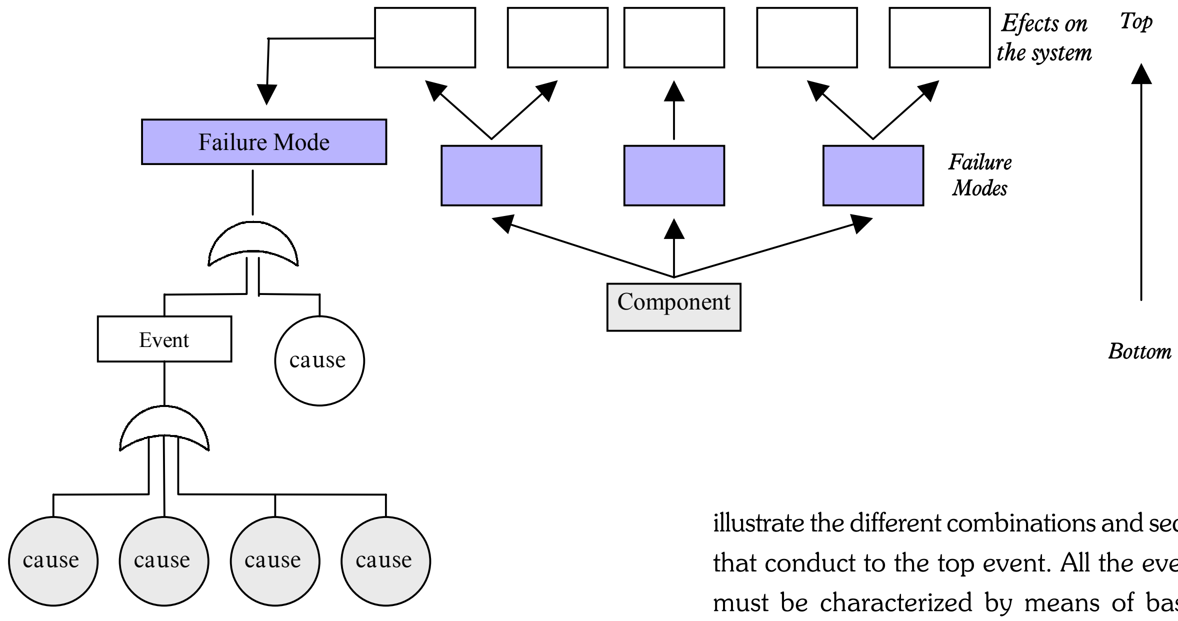

Figure 1: Block Diagram of the FTA and FMEA (SAKURADA, 2001)

According to RAMAKUMAR (1993), the following procedures must be conducted for the implementation of a FTA: 1) Identifying the undesirable event or failure condition denominated top event for the system under analysis; 2) Studying and understanding the system under analysis, as well as the purpose for which it has been designed; 3) Determining the functional events of higher order which may cause an undesirable failure, and also the logical relationships between events of a lower order that may produce functional events of a higher order; 4) Constructing a fault tree using the set of basic structure blocks. This tree must graphically illustrate the different combinations and sequences of events that conduct to the top event. All the event failure entries must be characterized by means of basic or functional failures, independent or secondary and identifiable or controlled; 5) Qualitatively and quantitatively assessing the fault tree, depending on the data available.

The Brazilian Association of Technical Standards ABNT, in the standard NBR 5462 (1994), defines FMEA (Failure Mode and Effect Analysis) as "a qualitative method for reliability analysis which involves the study of the failure modes that can exist in every sub-item, and the determination of the effects caused by this failure modes over other sub-items and over the required function of the item". The association of the tools FMEA and FTA has allowed the creation of the database containing the main failure modes, Table 1.

Table 1: FMEA of the main failure modes applied to compressors

Sub-system	Function	Component	Function	Failure Mode	Effect	Cause
Suspension system and limiter of oscillating motion	Reduce the vibration and noise transmition from the kit to the compressor body and refrigeration system	Helical spring	Suspend the mechanical kit in the compressor	No fixing	Noise / Vibration out of normal standard	Error in the spring support assembling (Point 3)
				Missing spring		
				Wrong spring (size, diameter, etc)	Noise / Vibration out of normal standard	Error in the spring assembling in the support (Point 21)
				Failed spring		
				Placed out of plastic knocker		
Suction system	Conduct the refrigeration gas to the system to be cooled, at low pressure and temperature, to the compression chamber	Muffer's spring (Suction chamber)	Press the muffler against the valve plate to avoid leakages	Wrong position	Noise / Vibration out of normal standard	Error in the kit head assembling (cover, gasket, muffler) (Point 21)
				Missing spring		

3. Fault Pattern

The Fault Pattern presented in this article has as objective the expression of the fault information identified through the tools FMEA and FTA. This novel association is valid in the methodological and scientific direction because it aggregates information contextualized in classes. These classes have information about the possible fault types detectable by noise levels and vibrations. These classes are the basis of sustentation of the entrance patterns. These entrance patterns come from the informational characteristics of the defect and contain the fault categories. A training set including these classes is then presented to the ANN (Artificial Neural Network).

3.1 Fault Pattern Characteristics

The measured signal in the time domain, as seen in Figure 1, passes by a functional block where it is transformed to the frequency domain trough the Fast Fourier Transforms and divided by frequency bands, as seen in Figure 2.

This procedure reduces a complex data set to subsets of simpler patterns generated from system data. In this article it was adopted an entrance pattern with twenty values corresponding to twenty frequency bands. It is known that defects are differentiated by presenting a particular frequency band. The energy of these bands is necessary for the occurrence of an automatic classification of the entrance vectors.

3.2 Pattern recognition

The pattern recognition can be defined as being the identification process by which certain structures are classified according to its characteristics, through comparisons between classes. The fault class mapping in any N-dimensional space, describes the attributes of the subspace by means of a vectorial representation of a class. The description of a pattern depicts the information contained in each category involved with the compressor fault recognition (DENCKER, 2002). Figure 3 shows this definition. The entrance vectors in the equation 1 express the fault classes of the subspace containing the variables x and y.

$$\Phi_m^x = [\phi(x_1), \phi(x_2)...\phi(x_n)] \quad \text{and} \quad \Phi_m^y = [\phi(y_1), \phi(y_2)...\phi(y_n)] \qquad (1)$$

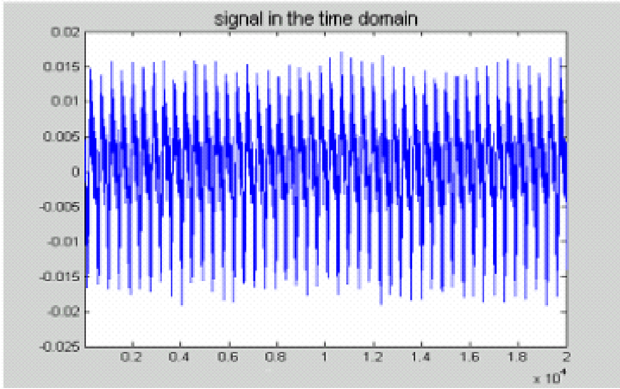

Figure 1: Example of signal in the time domain

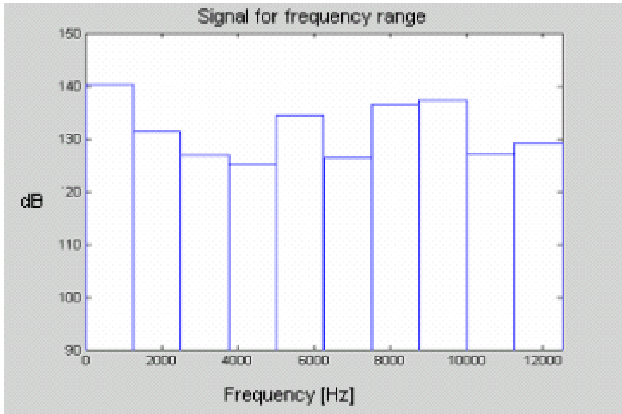

Figure 2: Signal for frequency range

These subspace variables describe the failure modes present in the compressors assembly line. The subindexes m and n describe the number of patterns containing the same failure mode and the same number of frequency bands, respectively.

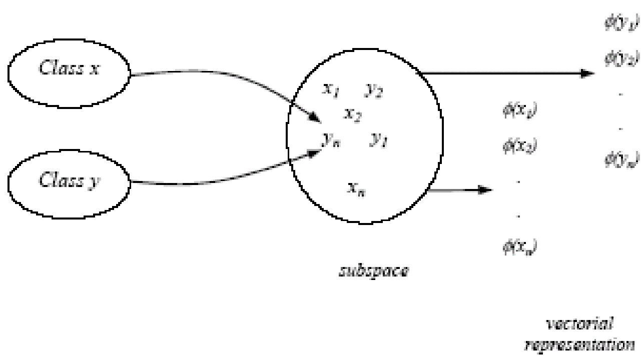

Figure 3: Class fault vectorial representation

3.3 Training patterns and tests

Known failure modes have been introduced in the compressors for the training and testing of the artificial neural network. These are the main failure modes found by the FMEA. This generated a fault database from which the net was off-line trained.

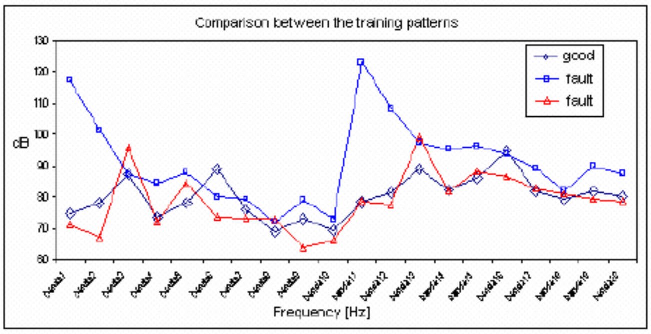

Figure 4: Comparison betwenn the training patterns

The focus of this study is on the fault analysis. After the ANN training, the panel starts to receive new data from the system. The model processes these patterns and the result shows the compressor quality. The quality is defined by working conditions. If the new entrance pattern is accepted as being one of the classes involved during the net training, the compressor may be accepted as "good" (approved), or "bad" and in this case it would be is segregated.

If possible the fault is fixed, if not, the compressor is rejected. But if the entrance pattern is not accepted a compressor might be approved even containing a fault.

This is the company's least desirable situation. On the other hand, the network can reject a good compressor. This compressor is tested again and if the pattern is a new one, there will have to be a retraining of the neural network with this new fault class.

To validate the model a comparative analysis will be done by constructing a network with the same characteristics of the current criterion. The vibration signals collected from the compressor carcass are used to the analysis.

These signals are transformed into the frequency domain and are divided in twenty values (Figure 4). The evaluation criterion of the current system is a comparison between the registered value and a reference value previously calculated.

Reached this limit the compressor is labeled as a defective one and it is necessary a more detailed evaluation. For a SPT (Statistical Performance Test) evaluation the following definitions were stipulated:

♦ **Definition one**: Every wrong result will be considered as a false approved, that is, all faults are harmful for a quality evaluation.

♦ **Definition two**: Every good compressor will be a truly approved.

♦ **Definition tree**: A good compressor that was refused will be a false segregated. The test detailing this process is shown in section 4.

4. ANN – Use and Implementation

Artificial Neural Networks (ANN) is parallel distributed systems composed by processing units that compute nonlinear mathematical functions. Normally, these processing units are disposed in layers and are linked by a great number of connections. Each connection is associated to a weight, which stores the knowledge learned by the net and serves to ponder the entrance received by each neuron of the net (DUARTE, 2000 and HAYKIN, 1999).

The signal analysis must be done in a fast manner to follow the speed of the daily production (CRISTALLI, 2000). To obtain some speed in the processing of noise and vibration signals it was used a multi-layer *feedforward* network (Z. L. KOVÁCS, 1996) trained with a quick propagation algorithm (VAZ, 1999). Loesch and Sari (LOESCH, 1996) suggested using the algorithm model with some modifications. The algorithm was implemented in MATLAB® language. The general topology in a macrostructure level used in this article (Figure 5) is about a strongly connected net, composed by a functional block, a classification layer, an identification layer and a rule basis layer.

The functional block objective is to prepare the data collected from the system, that is, to make them simpler through the Fourier Transform. The classification layer contains all the fault characteristics involved to be discriminated. Once a fault is classified, an identification layer describes the fault modes, which are presented by a rule basis.

The model considered for this article, for both the classification layer and the identification layer, is based on the *perceptron* created by Frank Rosenblatt, in 1957 (Z. L. KOVÁCS, 1996), in which the model has multiple neurons arranged in multiple layers with feedforward connections.

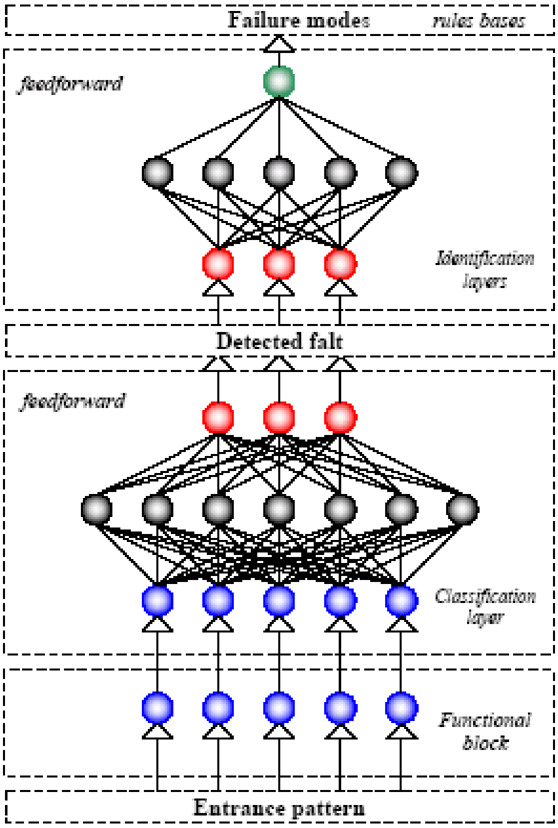

Figure 5: Proposed topology for neural network

The ANN showed in Figure 5 were submitted to the stages of training and test. In the training stage, the patterns normalized by frequency band have been presented to the net as entrance vectors. The net layers process this information and the resultant vector is compared with the desired one. These entrance and resultant vectors are the training pairs of the ANN. This process generates the average quadratic error. When the error margin is higher than the specified value, it means that the net did not learn this set of vectors or a specific vector. This error is then back propagated in the way that the weight matrix elements are updated. In this case the training corresponded to the characteristics of 100000 cycles, a moment of 0,3 and a learning rate of 0,1.

5. Results

The developed model, called Neuro Acoustic and Vibration System for Quality Control (SISNAV), aims at making easier the failure mode analysis by means of MATLAB® programming. Figure 6 shows the sequential procedure of analysis.

The module analyzes the sound pressure from the socket and the compressor carcass vibrations. An initial data treatment is one of the most relevant factors to the final efficiency of the classification process. The entrance patterns constitute a knowledge base that must be fed continuously, because the more complete these patterns are, the more information the net will extract.

As seen in Figure 6, the current compressor assembly line measurement panel collects the signals. The signal's FFT (Fast Fourier Transform) is stored in a database where these patterns are used for the off-line training of the ANN. After all the nets are trained, new compressors are measured and analyzed. The SISNAV will generate a report describing the compressor quality with the possible fault causes and assembly places where the fault was generated.

The SISNAV Interface was developed with the intention of organizing the model tests by simulating a panel of tests. Figure 7 shows one of the interface screens. The language MATLAB® version 6.1 was used in the programming. There is some edition buttons in this screen. Some parameters must be defined before running the program. *File* indicates a particular file name to be analyzed. This file is always necessary when the program is executed in the manual option. The next step is to define the compressor model for the analysis and then the program will keep this model as default.

The *compressor model* button will execute this function. The *Failure Mode* button contains only one list of the failure modes implemented in the database. For an automatic execution the *Auto processing* button must be activated.

This function loads all the files that were previously recorded by the measurement panel. The *Save log* button

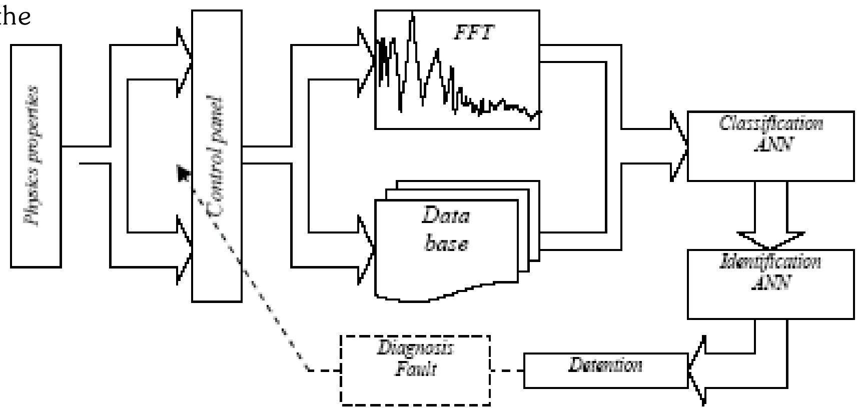

Figure 6: Sequential analysis procedure (SISNAV interface)

executes the recording of a report with extension *.txt* containing the file name, the neural network entrance pattern and the failure mode code. This report can be generated in the automatic and manual mode. The *START* button executes the program.

The main menu appears when this button is activated in the manual mode. This menu is composed of: frequency signal visualization (*Frequency domain graph*), visualization for frequency band (*Frequency band graph*), identification of the existence or not of a fault (*Neural network*), loading of a new file (*Load file*) and exiting the program (*Exit*). The Neural network submenu is composed of: quality compressor verification (*Failure mode*), returning to visualization submenu (*Back*) and exiting the program (*Exit*).

When the Failure mode button is activated a message containing the failure mode and a note with the possible places where the fault occurred is shown. The information of this message box was based on the FMEA and on the operator experiences. Finally, Figure 8 shows the quality of the measured compressor with the emission of a warning message. This message contains the necessary information that can be computed in an occurrences database. The operator verifies if this message is authentic. Once the failure mode was confirmed, the information is stored in an occurrence database as a checklist.

5.1 Statistical Performance Test (SPT)

The obtaining of data with a certain level of precision and the need of quantifying the decisions taken by the net leads to an effective and secure diagnosis. The information from the net testing takes us to probabilistic values that describe some uncertainties of the values, confirming or refuting the presence of a potential fault. The effectiveness in identifying how adequate is a test to determine the presence or absence of fault in the compressor is given by the results produced from the evaluated system that does not only depend on sensitivity and specificity, but also on the presence of the real fault during the test.

The criterion-based validity of a fault is statistically estimated, and it is expressed through its sensitivity (ratio of segregated cases identified correctly), specificity (ratio of approved cases identified correctly), the Approved Predictive Value (APV), that indicates the probability of the approved cases detected being really approved, the Segregated Predictive Value (SPV), that indicates the probability of cases detected as segregated being really segregated (Menezes, 1998). The foundation of this analysis is following a set of compressors in the production line while paying attention to those characteristics.

The number of files tested amount to 82. During the tests the current panel rejected a good compressor, justifying the value of 98,3% for specificity. The 66,7% sensitivity indicates the capacity of the test in detecting a defective compressor. The reason for that is the approval of 8 defective compressors. These 8 compressors are undesirable because they will reach the market.

The APV calculated is 87,6%, it is the probability that a compressor with approved result does not have the fault. And the probability of a compressor with a segregated result has the fault is defined by the Segregated Predictive Value, which is 94% in this case. On the other hand, the system considered for these compressors achieved 100% in the SPT indices, demonstrating its potentiality in the compressors fault segregation.

6. Conclusion

In a general way, the neural network implementation for compressor fault identification is very satisfactory since the entrance patterns are very approximate. The use of a classification neural network and an identification net containing binary values (0 and 1) in the entrance patterns increased the result generalization capacity. Even if the neural network has not a completely exact exit vector, the identification neural network shows its capacity of presenting the results correctly.

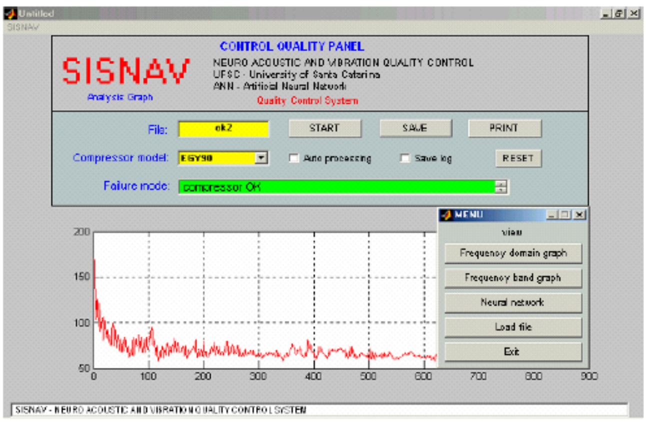

Figure 7: SISNAV screen (submenu visualization): Signal example in the frequency domain

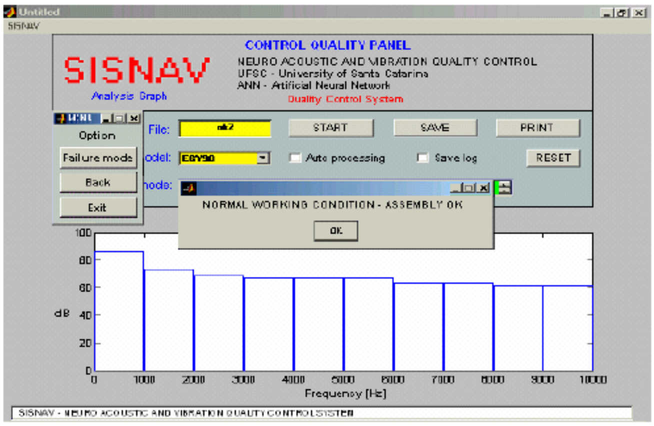

Figure 8: SISNAV screen: Failure mode and its causes

This system integrates an evaluation that pays attention to the reduction of the occurrence level, acting indirectly in the whole production line. In this situation the system tends to correlate an imperfection with the line assembly sectors, creating a kind of quality cycle.

Reports of each measurement are presented indicating the possible causes responsible for the failure occurrence. The failures information is extracted from the FMEA and the FTA.

The occurrence inside any system indicates the path where stronger efforts are needed. As the occurrence of the defect reflects, most of the times, the reality of the process, the joint performance of the process-fault-operator is indispensable to ensure a product of good quality.

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