METHODOLOGY TO EVALUATE THE QUALITY CONTROL IN THE COMPRESSOR ASSEMBLY LINES

Fabiano Alves Dencker
LVA, Departamento de Eng. Mecânica, UFSC
Cx. Postal 476 – Trindade
CEP 88040-900 Florianópolis – SC Brasil
fabianodencker@ig.com.br

Arcanjo Lenzi, Acires Dias
LVA, Departamento de Eng. Mecânica, UFSC
Cx. Postal 476 – Trindade
CEP 88040-900 Florianópolis – SC Brasil
arcanjo@emc.ufsc.br , acires@emc.ufsc.br

Abstract: *This paper concerns in a methodology development to evaluate the quality control in the compressor assembly lines. Here it's deal with the tools of Artificial Neural Network (ANNs), Failure Mode and Effects Analysis (FMEA) and Fault Tree Analysis (FTA). Based on this approach there are the proposals of: main failure modes in the compressors assembly line analysis and automatic identification of this cases through neural networks. The objective is reduce the number of assembled wrong compressors under the enterprise recommended standards. This proposal aim to extract feature of a primitive signal through installed sensors in the measurement panel and classify with a Neural Network signs of perfect or defective compressors. To evaluate the proposal the obtained results are compared with the actual system of measurement. The rightness index of the proposed model is between 97% and 100% of correctly patterns identification.*

Keywords: *quality control, assembly line compressors, artificial neural network, and failure modes*

1. 1. Introduction

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

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

2. Fault Pattern

The Fault Pattern presented in this article has the objective to express the fault information identified through the tools FMEA and FTA. This new association is valid in the methodological and scientific direction because it adds information in classes. These classes have information about the possible fault types detectable by noise levels and vibrations. These classes are the sustentation bases of the entrance patterns. These entrance patterns come from the information characteristics of the defect and contain the fault categories. Then, a training set including these classes is presented to the ANN (Artificial Neural Network).

2.1. Fault Pattern Characteristics

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

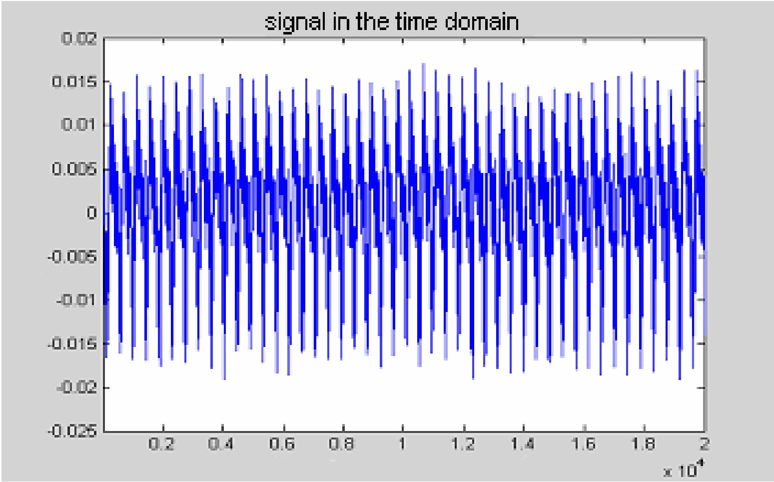

Figure 1. Example of signal in the time domain

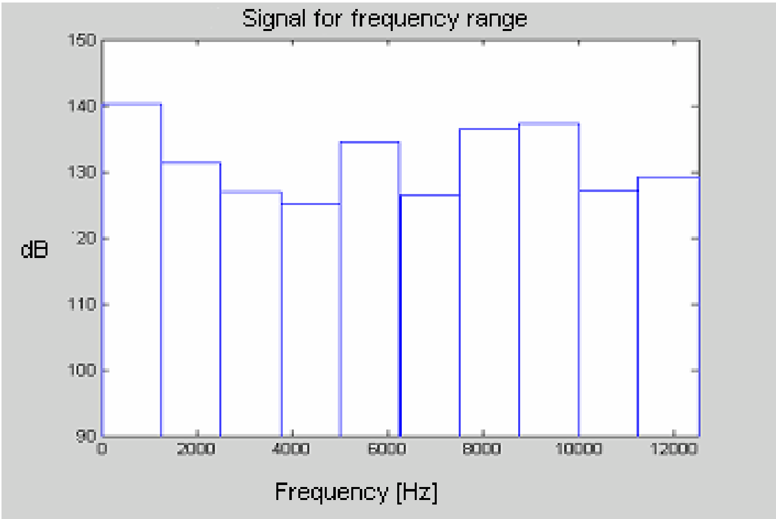

Figure 2. Signal for frequency range

This procedure reduces a complex data set in simpler pattern subgroups generated from system data. In this article was adopted an entrance pattern with twenty values for twenty frequency bands. It is known that defects a present by differentiated frequency band, this way they can be differentiated. The energy of these bands is necessary to occur an automatic classification of entrance vectors.

2.2. Pattern recognitions

The pattern recognitions can be defined as being the identification process for which they classify certain structures for its characteristics, through comparisons between classes. The fault class mapping in any N-dimensional space, it describes the subspace attribute by means of a class vectorial representations. The pattern description describes the information contained in each involved category in the compressor fault recognition (Dencker, 2002). Figure 3 shows this definition. The entrance vectors in the equation 1 expresses the subspace fault classes including x and y variables.

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

These subspace variables describe the present failure modes in the compressors assembly line. Then, *m* and *n* describes the pattern numbers which contain the same failure mode and the frequency band numbers, respectively.

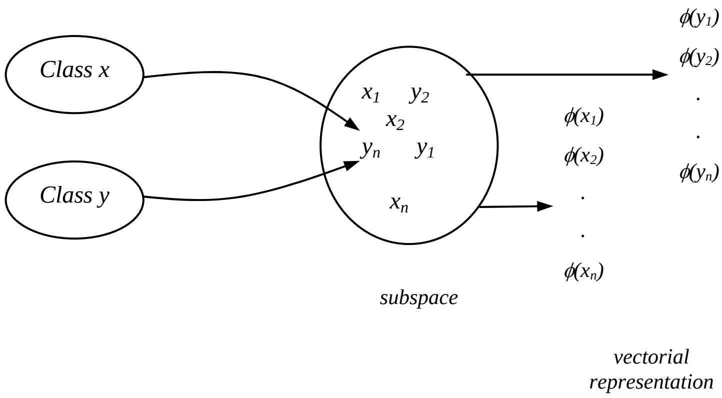

Figure 3. Class fault vectorial representation

2.3. Training patterns and tests

Failure modes have been produced in the compressors for the artificial neural network training and test. The FMEA finds these failure modes more frequently. This generated a fault database in which the net was off-line trained.

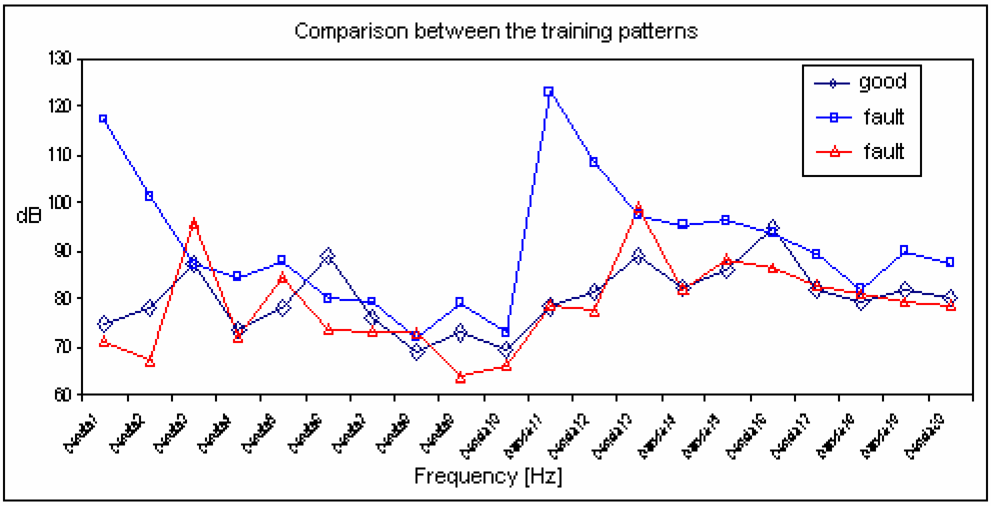

Figure 4. Comparison between the training patterns

The focus of this study is the fault analysis. After the ANN training, the panel starts to receive new data from the system. The model works these patterns and the result shows the compressor quality. The quality is defined by working conditions. If the new pattern entrance was accepted as being one of the involved classes during the net training, the compressor would be accepted as “good” (approved), or else “bad” and on this case it would be segregated. If possible, the fault would be corrected or else the compressor will be rejected. But if the entrance pattern is not accepted a compressor can be approved even with fault. This situation is what the company does not want. On the other hand, the network can reject a good compressor. This compressor is tested again and if it is a new pattern, we will have to training again the neural network with this new fault class.

To validate the model a comparative analyze will be done from constructing a network with the same characteristics of the current criterion. The vibrations signals come from the compressor carcass are used to analyze. These signals are transformed into the frequency domain and are divided in twenty values (Figure 4).

The currently evaluation criterion is a comparison of the read value with a reference calculated previously. Reached this limit the compressor is labeled as a defective one and it is necessary an evaluation more detailed. For a SPT (Statistical Performance Test) evaluation is stipulated the following definitions:

Definition one – All wrong result will be considered as a false approved, or, all faults are harmful for a quality evaluation.

Definition two – All good compressor will be a true approved.

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

3. ANN – Use and Implementation

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

The signal analyze must be done fast in order to deal the daily production (Cristalli, 2000). To get some speedy in the vibration and noise signal processing it was used a multi-layers *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 net well connected, composed with a functional block, a classification layer, an identification layer and a rule bases layer.

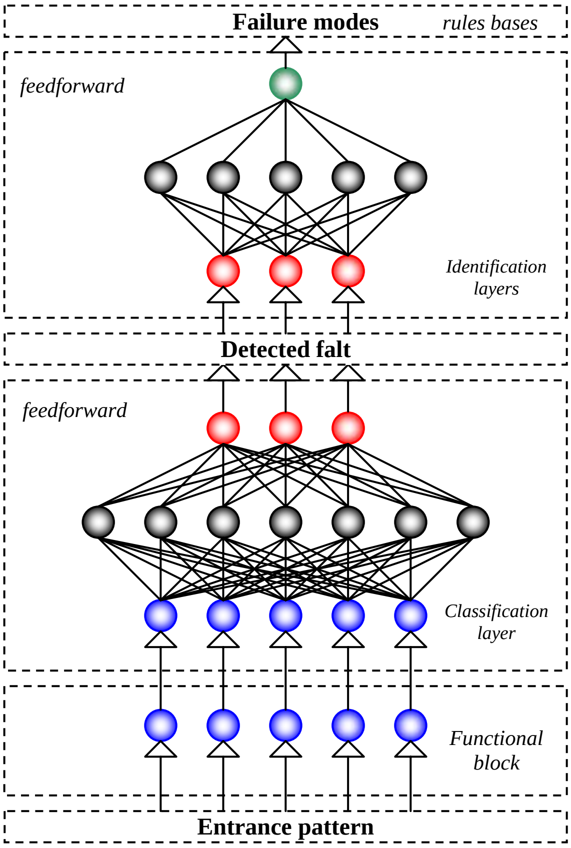

Figure 5. Proposed topology for neural network

The functional block objective is to prepare the collected data from the system, in other words, to make them simple through the Fourier Transform. The classification layer contains all the involved fault characteristics to be discriminated. Once a fault is classified, an identification layer describes the fault modes, which are presented for a rule bases.

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

The ANN showed in Figure 5 was submitted to the training periods and tests. In the training, the normalized standards for frequency band have been presented to the net as entrance vectors. The net layers process this information and the result vector is compared with the desired one. These entrance and result vectors are the training pairs of the ANN. This process generates the average quadratic error. When the error margin is bigger than the specified value, it means that the net did not learn these vectors group or a specific vector. Then, this error is 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 tax of 0,1.

4. Results

The developed model, called Neuro Acoustic and Vibration System for Quality Control (SISNAV), aims to make the failure mode analysis in MATLAB® programming easier. Figure 6 shows the sequential analysis procedure.

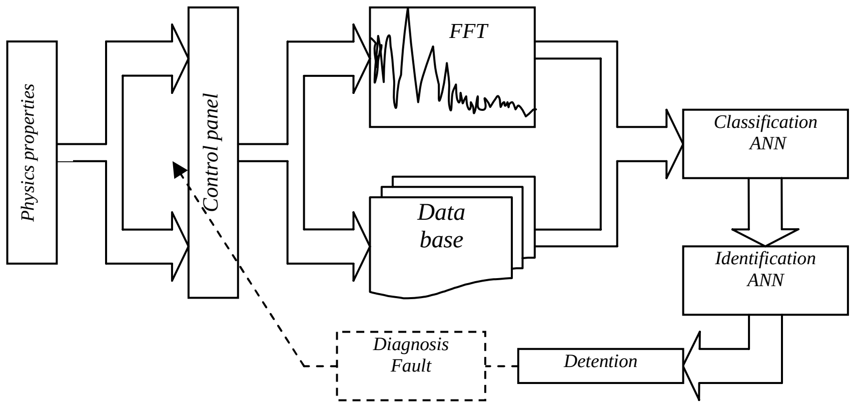

Figure 6. Sequential analysis procedure (SISNAV interface)

The module analyzes the sound pressure from the socket and the compressor carcass vibrations. An initial data treatment is a very important point in order to get a good result in the final of the classification process. The entrance standards form a knowledge base that must be feed continuously, because as more complete these standards are, 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 standards are used for the off-line training of the ANN. After the all-net training, the new compressors are measured and analyzed. The SISNAV will generate a report describing the compressor quality with the possible fault reasons and places where the fault was generated.

The SISNAV Interface was developed with intention to organize the model tests simulating a test panels. 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 run program. *File* indicates a particular file name that we want analyze. 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 be keep this model as a standard. The *compressor model* button will execute this function. The *Failure Mode* button contains only one list of the implemented failure modes in the database. For an automatic execution the *Auto processing* button must be activated. This function loads all the previously files that were recorded by the measurement panel. The *Save log* button executes the recording of a report with extension *.txt* including 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. A principal 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)*, load a new file (*Load file*) and quit the program (*Exit*). The Neural network submenu is composed of: quality compressor verification (*Failure mode*), come back to visualization submenu (*Back*) and quit the program (*Exit*).

When the Failure mode button is activated a message including 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 measured compressor quality emitting a warning message. This message contains 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 was stored in an occurrence database as a checklist.

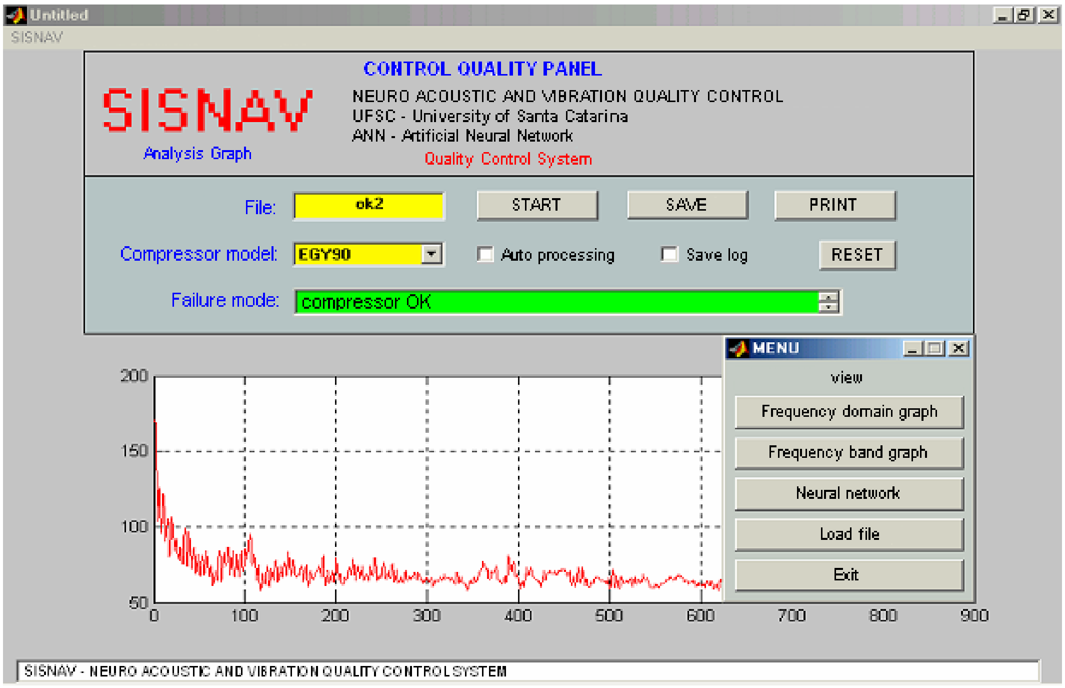

Figure 7. SISNAV screen (submenu visualization): Signal example in the frequency domain

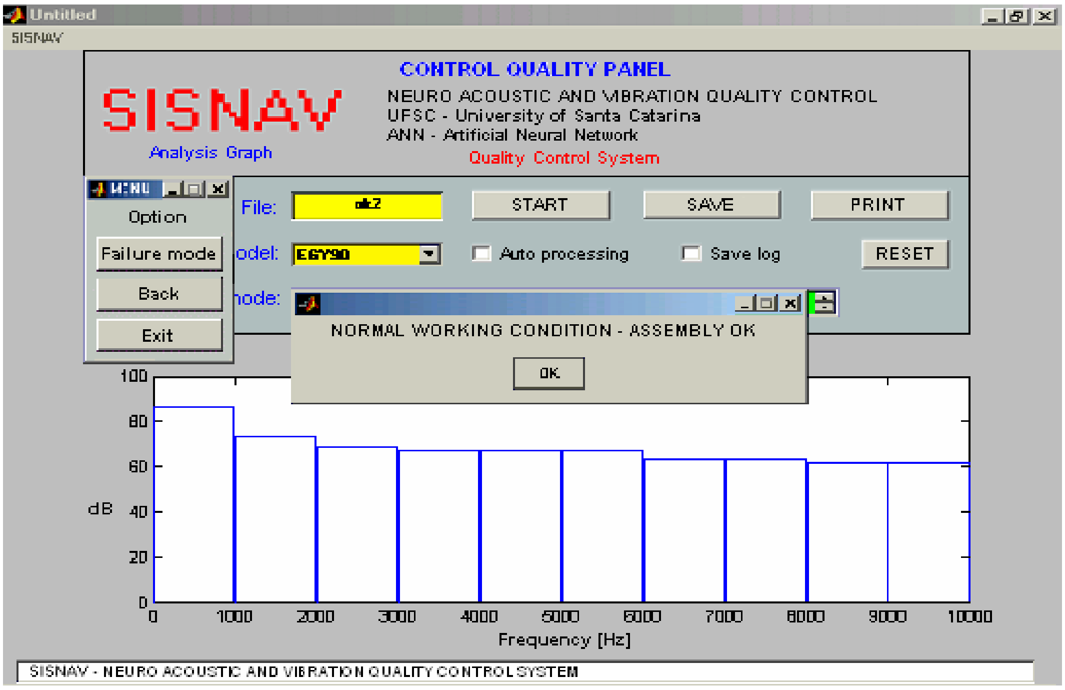

Figure 8. SISNAV screen: Failure mode and its causes

4.1. Statistical Performance Test (SPT)

In order to get a safely diagnosis was needed to have a more exact data as possible and to quantify the net decisions. 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 if a test is good to determine the presence or absence of fault in the compressor is given through the results produced from the evaluated system that does not only depend on sensitivity and specificity, but also of the real fault presence during the test.

The fault criterious is statistically estimated, and it was 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 really be approved, the Segregated Predictive Value (SPV), that indicates the probability from that detected cases as segregated really must be segregated (Menezes, 1998). To follow a compressors group in production line attempting against the supplied characteristics is the foundation for this analysis.

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

The APV calculated is 87,6% that is the probability of 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 Segregated the Predictive Value, and is 94% in this case. On the other hand, the considered system for these compressors achieved 100% in the SPT indices, demonstrating its potentiality in the compressors fault segregation.

5. Conclusion

In a general way, the neural network implementation in the compressor fault identifications are very satisfactory, in order of the entrance standards nearness. The use of a classification neural network and a identification net contending binary values (0 and 1) in the entrance standards increased the result generalization capacity. Even if the neural network has not an exit vector completely exact, the identification neural network shows its capacity of presenting the results correctly. This system integrates an evaluation that intent for the occurrence level reduction, acting indirectly in the whole production line. In this situation the system tends to correlate an imperfection with the line assembly sectors, doing a kind of quality cycle.

Reports to each measurement are presented showing the possible causes that were responsible for the imperfection occurrence. The occurrence inside of any system describes an indicative of the way where it is necessary strong efforts. How the defect occurrence reflects, in the majority of the times, the reality of the process, the joint performance of the process-fault-operator is indispensable to ensure a good quality of product.

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