Use of Competitive Neural Network to Acceptance of Compressors in Assembly Line

Júlia Bertelli Duarte¹, Marcus Antonio Viana Duarte², Marlipe Garcia Fagundes Neto³

¹Universidade Federal do Triângulo Mineiro, 1250, Avenida Doutor Randolfo Borges Júnior, 38064-200, Uberaba, Brazil
²Universidade Federal de Uberlândia, 2121, Avenida João Naves de Ávila, Bloco 1M, 38408-100, Uberlândia, Brazil
³Universidade Federal de Goiás, 1488, Avenida Universitária, Quadra 86, 74605-010, Goiânia, Brazil

Abstract—Rotary compressors are equipment, which are broadly applied in industrial installations, refrigerators and air conditioner systems. In other hand, the noise generation mechanism from these compressors is rather complex, comprising almost all the audible spectrum. The product quality control, within NVH limits, is still subjective and depends on the operator experience. In this paper, a competitive neural network was used and trained by vibrating symptoms, in order to remove the process’ subjectivity. A group of compressors with manufacturing defects is set up, which are refused by clients in matter of noise, and a group of compressors, which are considered good by the end customers in order to test the methodology. Results show that the competitive network, when well trained, and considering the data measured in a weld point, can be used as a quality control system.

Keywords—competitive neural network, rotary compressors, quality control, vibration.

I. INTRODUCTION

Compressors are devices widely used in industrial installations, as they serve to increase the pressure of a gas through its compression, generating compressed air, for example. Rotary compressors are alternative and volumetric compressors type, i.e., they reduce the occupation volume of gas to achieve an increase in pressure. Typically, they are used for applications that do not require large amounts of flow, such as air conditioning for residential use.

According to [1] the sound generated by rotary compressors depends on the rotation frequency and its multiples, the number of rolling elements, the flow capacity and other factors related to the flow, being the main generated by varying the pressure created between the compressor suction and discharge. [2] already defines as major sources of noise from a rotary compressor, internal turbulence, the impact of the valves, friction and electric motor.

The industries have as a major challenge the establishment of reliable criteria for the quality control of their products and services.

The human ear despite being a highly sensitive and widely tool used in quality control, it is sensitive to emotional and environmental problems (background noise, for example), and does not result in measurable values, both requested and required by current testing standards as ISO9000 and QS9000.

In order to quantify and identify the subjective parameters to classify and define the quality of the final product, we want to develop analytical, computational and experimental procedures based on signal analysis and neural networks to be used as a support tool in the quantification and identification of possible sources of noise in compressors.

The signal analysis, statistically based, is widely used to detect faults and equipment failures, and there are even patents generated for these analyzes. [3] developed a patent to protect a method, computer program, and system for real-time signal analysis providing characterization of temporally-type signals in a moving time window by tracking output of order statistic filters (also known as percentile, quantile, or rank-order filters). The invention, given a raw input signal, enables automated quantification and detection or changes in the distribution of any set of quantifiable features of that signal as they occur in time, among other things.

Due to its popularity attributed to the fact that it has been successfully applied to a wide variety of problems, competitive neural networks are a type of artificial neural network, unsupervised, and have been used to construct a compact statistical representation of a data set input not labeled, i.e., are able to recognize patterns and common extracting statistically significant features from the input data. [4] have proposed to diagnose urban rail vehicle auxiliary inverter faults based on wavelet packet neural network and genetic algorithm.

II. METHODOLOGY

At first is necessary observe if exist some correlation between client’s subjective perception and the noise generated by compressor.
In affirmative case, then it is possible to define vibroacoustic symptoms to be used as "go/no go" testing in assembly line.

To do this analysis, two sets of compressors were chosen: one compound by good baseline compressors and another compound by compressors where "manufacturing defects" were introduced for study purpose. Then the compressors were sent randomly to be tested by two customers that classified them as acceptable compressors (Good) and faulty compressors (Bad) on emitted noise criterion. Finally, the sound power levels was measured in a semi-anechoic chamber, according to [5].

A. Sound Power Levels Measurement SWL

Twenty values of SWL were measured in 1/3 octave bands (from 100 to 10000 Hz) and two overall values (linear and A ponderation filter). Those values with RMS values of the motor drives resulted in 24 symptoms to be analyzed.

B. Estimation of Means and Sample Standard Deviation

After measured all SWL symptoms of the compressors grouped as Good and Bad by the costumers, the average, and respective standard deviations, were estimated for each one of the two sets.

C. Chauvenet’s Criterion

This criterion was applied only for the Good set, since does not want a large variance inside this lot, and consisted in eliminating the compressors for which various values of symptoms were greater than the ratio d/scritic. The criterion was used only for values of d above the average sample value.

D. Comparison of Populatuion Means

To compare the mean values of the two populations (Good and Bad Compressor) there will be a homocedasticity test to define what hypothesis’s test on equal populations will be use.

To test the two-tailed alternative $H_0$: $\sigma_1=\sigma_2$ e $H_1$: $\sigma_1\neq \sigma_2$, uses the fact that the statistics shown by Eq. (1) is distributed as an F distribution with $n_1$-1 e $n_2$-1 degrees of freedom, if the null hypothesis $H_0$ is true.

$$F_0 = \frac{S_1^2}{S_2^2}$$  
(1)

Therefore, $H_0$ will be rejected if Eq. (2) is true.

$$F_0 > F_{1-\alpha/2,n_1-1,n_2-1}$$  
(2)

A significance level ($\alpha$) of 5% was used in all hypothesis tests.

In order to define if a vibroacoustic symptom can or cannot be used in the compressors classification in question noise, a test for difference between population means (t-test) with null hypothesis of $\mu_1 - \mu_2 = 0$ was used. Homoscedasticity tests were carried out to define the t-test used.

If the null hypothesis is true, the variables $t_{homo}$ e $t_{hetero}$, calculated by Eq. (3) e Eq. (4), have a t-Student distribution for $\mu_1 = \mu_2$.

$$t_{homo} = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\left(\frac{1}{n_1} + \frac{1}{n_2}\right)\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)}}$$  
(3)

$$t_{hetero} = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$  
(4)

Where:

- $n_1$ e $n_2$ are the sample sizes 1 e 2, respectively; $ar{X}_1$ e $ar{X}_2$ are the sample mean; $s_1$ e $s_2$ are the sample standard deviation; $t_{homo}$ is used by test with homoscedastic sample with $n_1$+2 degrees of freedom; and $t_{hetero}$ is used by test with heteroscedastic sample with g degrees of freedom, calculated by Eq. 5.

$$g = \frac{\left(\frac{s_1^2}{n_1}\right)^2 + \left(\frac{s_2^2}{n_2}\right)^2}{n_1 + 1 + \frac{n_1}{n_2 + 1}}$$  
(5)

After checking that there are a correlation between the subjective perception of costumer and the SWL values, the vibration signals were acquired in two distinct points, as show in the Fig. 1, for all tested compressors. In this work the points 1 and 2 are measurements points in a weld point and on the cap, respectively.
The symptoms analyzed in this work were:

- 16 symptoms of electric motor harmonics;
- 25 symptoms of 1/3 octave bands (from 40 to 12500 Hz);
- 18 symptoms of envelope analysis vibrations;
- 17 symptoms of synchronous time domain average using acceleration signals;
- 16 symptoms of time synchronous domain average using velocity signals;
- 13 symptoms on time domain such as RMS, kurtosis, cestrum and etc., using acceleration signals;
- 13 symptoms on time domain such as RMS, kurtosis, cestrum and etc., using velocity signals;

The large number of symptoms for each analysis procedures is due to use of frequency filter for various bands of signals of acceleration and velocity.

The signal analysis procedure consists in:

- The visual analysis - by boxplot - of vibroacoustic symptoms of the two sets of compressors were used to a initial definition of the best symptoms to be used in a "go/no go" based on noise criterion. It is important to alert that in analyzing of boxplot diagrams, the box and the median of symptoms of group Good should be located far below the Bad one;
- Comparison, through t-test to select the best parameters of noise and vibration to be used as symptoms for rotary compressors quality control.

### E. Use of Neural Network

By having the calculated values of symptoms, a MATLAB® routine is used for the competitive neural network, and the input data are the symptoms themselves.

After creating the network via newc command with two neurons in the competitive layer, the neural network must be trained. Simulating the network, first evaluated if the symptoms of good compressors are classified as a group, and then the same is done for the symptoms of bad compressors.

For symptoms that the network recognizes as a group with determining characteristics, an analysis of population means is proposed and then chooses the best parameters to be used as symptoms.

Finally, the two analyses methods were compared (signal analysis and neural network) in order to choose the best point to measure and verify the effectiveness of the network in defining the symptoms.

### III. RESULTS AND DISCUSS

After SWL measurements, the use of Chauvenet criterion resulted in the elimination of one compressor of the set of compressors considered good. Consequently, eleven signals of good compressors and fourteen with problems composed the two dataset.

In Tab. 1 are listed 24 symptoms studied and the reasons $F/F_{0.975,12,12}$ used in homoscedastic test. To get a balanced test two signals of Bad group were randomly removed of the analysis.

### Table 1. Homoscedasticity test.

<table>
<thead>
<tr>
<th>Symptom</th>
<th>$F/F_{0.975,12,12}$</th>
<th>Symptom</th>
<th>$F/F_{0.975,12,12}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 Hz</td>
<td>4,39</td>
<td>1600 Hz</td>
<td>2,48</td>
</tr>
<tr>
<td>125 Hz</td>
<td>2,16</td>
<td>2000 Hz</td>
<td>1,12</td>
</tr>
<tr>
<td>160 Hz</td>
<td>2,03</td>
<td>2500 Hz</td>
<td>2,14</td>
</tr>
<tr>
<td>200 Hz</td>
<td>2,68</td>
<td>3150 Hz</td>
<td>2,62</td>
</tr>
<tr>
<td>250 Hz</td>
<td>2,00</td>
<td>4000 Hz</td>
<td>1,48</td>
</tr>
<tr>
<td>315 Hz</td>
<td>1,22</td>
<td>5000 Hz</td>
<td>1,86</td>
</tr>
<tr>
<td>400 Hz</td>
<td>1,62</td>
<td>6300 Hz</td>
<td>1,99</td>
</tr>
<tr>
<td>500 Hz</td>
<td>6,71</td>
<td>8000 Hz</td>
<td>1,90</td>
</tr>
<tr>
<td>630 Hz</td>
<td>10,34</td>
<td>10000 Hz</td>
<td>0,46</td>
</tr>
<tr>
<td>800 Hz</td>
<td>2,78</td>
<td>dB(L)</td>
<td>3,29</td>
</tr>
<tr>
<td>1000 Hz</td>
<td>1,19</td>
<td>dB(A)</td>
<td>2,99</td>
</tr>
<tr>
<td>1250 Hz</td>
<td>0,96</td>
<td>Current</td>
<td>1,52</td>
</tr>
</tbody>
</table>

From the analysis of Tab. 1, it is observed that only in two frequency bands (1250 and 10000 Hz), the two samples have the same variance ($F/F_{0.975,12,12} < 1$).
The high ratio values observed for bands of 500 Hz and 600 Hz indicates a high nonconformity among the signals of the refused compressors group.

In Tab. 2 are listed the 24 symptoms studied and respective reasons of the t-test for 5% level of significance. It can be observed that the greatest differences between means were for frequency bands centered between 315 and 500 Hz, and the bands centered at 800 and 6300 Hz. It is interesting to note also that the hypothesis testing was refused for the overall values dBL and dB(A). It should be emphasized that the dB(A) curve is a good estimator of the auditory sensation of the human ear.

The sum of the noise energy levels in the bands from 315 to 500 Hz results in a symptom value of \( \frac{t}{t(0.95, 24)} \) equal to 4.35, i.e., an excellent symptom to evaluate the quality of the acoustic compressors studied.

Table 3 shows the best analyzed symptoms and respective \( \frac{t}{t(0.95, n)} \) ratio for measurement point 1 where all values are in dB scale (reference 1.0 measure unit). Due to pages limitation, the results will be shown only to the best measurement point. The best result for the symptoms is Envelope 18. Figure 2 shows the boxplot diagram for such symptom.

\[
\begin{array}{|c|c|c|}
\hline
\text{Symptom} & \text{Description} & \frac{t}{t(0.95, 24)} \\
\hline
\text{Motor 2} & \text{Second set of harmonics of stator slots} & 2.08 \\
\text{Motor 16} & \text{Octave set of harmonics of rotor slots} & 2.16 \\
\text{Envelope 12} & \text{Overall amplitude of envelope (high pass 6000 Hz filter)} & 1.99 \\
\text{Envelope 14} & \text{Overall amplitude of envelope (high pass 8000 Hz filter)} & 2.15 \\
\text{Envelope 16} & \text{Overall amplitude of envelope (high pass 10000 Hz filter)} & 2.42 \\
\text{Envelope 17} & \text{Energy level of envelope (high pass 12000 Hz filter)} & 2.54 \\
\text{Envelope 18} & \text{Overall amplitude of envelope (high pass 12000 Hz filter)} & 2.79 \\
\text{Time 3} & \text{Kurtosis} & 1.78 \\
\text{Time 4} & \text{Crest factor} & 1.68 \\
\text{Time 5} & \text{K4 (10log_{10}(RMS*Curtose))} & 1.80 \\
\hline
\end{array}
\]

It is observed, in Fig 2, a difference of 2 dB between the medians and the fact that values outside the mustache does not exist, i.e., there are no values far away from the median. It is also observed that the interquartile range (blue box) is narrower and is far between which makes this symptom very good to be used in the assembly of a go/no go mask.

**Figure II. Boxplot diagram for the symptom Envelope 18.**
It is noteworthy that the medians of some symptoms had good difference in boxplot diagram, but the existence of values outside mustache disapproved those symptoms. Figure 3 shows the boxplot diagram to better symptom calculated for the higher harmonics of the electric motor: Motor 16. By analyzing the figure, we note that the difference of the medians is 6 dB, and the third quartile of Good set does not intersect with the first quartile of the Bad ones. This makes it an excellent symptom to quality control based on vibratory signals.

Figure 3. Boxplot diagram for the symptom Motor 16.

Figure 4 shows the boxplot diagram for the best symptom in the time domain, which was the Time 5 of acceleration signal.

In Fig. 4 it is observed that the variation of the median is very small, about 1 dB. In this case the difference between the two sets mean can be explained by interquartile amplitudes which having a variation of approximately 1 dB too.

In Tab. 4 are listed the best results obtained with neural network to point 1.

By comparing Tab. 3 and Tab. 4 it is noted that many symptoms have been identified by both techniques. This shows that neural network can detect good symptoms to be used as a go/no go criterion.

<table>
<thead>
<tr>
<th>Symptom</th>
<th>Description</th>
<th>$t_{0.95,n}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motor 2</td>
<td>Second set of harmonics of stator slots</td>
<td>2.08</td>
</tr>
<tr>
<td>Motor 16</td>
<td>Octave set of harmonics of rotor slots</td>
<td>2.16</td>
</tr>
<tr>
<td>Envelope 10</td>
<td>Overall amplitude of envelope (high pass 4000 Hz filter)</td>
<td>1.68</td>
</tr>
<tr>
<td>Envelope 14</td>
<td>Overall amplitude of envelope (high pass 8000 Hz filter)</td>
<td>2.15</td>
</tr>
<tr>
<td>Envelope 16</td>
<td>Overall amplitude of envelope (high pass 10000 Hz filter)</td>
<td>2.42</td>
</tr>
<tr>
<td>Envelope 17</td>
<td>Energy level of envelope (high pass 12000 Hz filter)</td>
<td>2.54</td>
</tr>
<tr>
<td>Envelope 18</td>
<td>Overall amplitude of envelope (high pass 12000 Hz filter)</td>
<td>2.79</td>
</tr>
<tr>
<td>Time 3</td>
<td>Kurtosis</td>
<td>1.78</td>
</tr>
<tr>
<td>Time 5</td>
<td>$K4(10\log_{10}(\text{RMS} \cdot \text{Kurtosis}))$</td>
<td>1.80</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

The main conclusions from this work were:

- There is a good correlation between the subjective noise perception of the costumers and the SWL values in 315 to 500 Hz band and 800 to 6300 Hz band;
- The main symptoms analyzed to the measured point 1 (near the weld) were: Motor 2, Motor 16, Envelope 12, Envelope 14, Envelope 16, Envelope 17, Envelope 18, Time 3, Time 4 and Time 5, with the $t_{0.95,n}$ values: 2.08; 2.16; 1.99; 2.15; 2.42; 2.54; 2.79; 1.78; 1.68 e 1.80, respectively;
- Neural network can detect good symptoms to be used as a go/no go criterion.

Acknowledgements

Research Support Foundation of Minas Gerais (FAPEMIG), National Council for Scientific and Technological Development (CNPq) and National Council for the Improvement of Higher Education (CAPES) for financial support. TECUNSEH for provide the compressors to analysis.
REFERENCES


