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# Sound Quality Evaluation of Hermetic Compressors Using Artificial Neural Networks

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## ABSTRACT

The increasing needs for research and development works on products noise reduction has lead to observations that A-weighted sound pressure and sound power measurements not represent customers perception about noise in a complete way. Sound quality metrics were developed for the psychoacoustic characterization of sound as it is perceived and provide an improved assessment since it considers more detailed contents in time and frequency domains. This work presents a sound quality analysis of noise generated by hermetic compressors. It was observed a close relationship between jury response, A-weighted noise levels, and loudness results obtained for this product. Jury results showed higher sensitivity to specific details of noise composition compared to current sound quality metrics. Jury analysis, however, is a more elaborated and time consuming procedure. In order to reduce such disadvantages an artificial neural network was developed and tested with the objective of representing the jury response to this class of product. Results are in reasonably good agreement with those obtained by a real jury. This has encouraged continuing the development of this technique.

## 1. INTRODUCTION

The sound quality of the noise from a product is of ever-increasing importance when assessing the total quality of the product. For products ranging from cars to household appliances, not only the level but also the quality of the noise it makes part of what attracts or repels the customer; the right sound can lead to increase sales. Many factors come into play in the sound quality evaluation process. Traditional objective measuring and analysis methods, such as A-weighted sound pressure and FFT analysis, are not enough to analyze product sound. Customer expectations and jury testing are also important factors for determining acceptable sound quality because, in the end, only the human ear can tell the designer whether or not the product has the right sound. Otherwise, it's necessary a respectable effort to make feasible a good and conclusive jury analysis. With the objective to decrease such disadvantages an artificial neural network was developed and tested in order to representing the jury response to this class of product. This relatively recent tool, the artificial neural network, shows great potential of appliance and works considerably well. A very good concordance was found between the jury analysis and the results of this new procedure.

## 2. METRICS OF PSYCHOACOUSTICS

The sound quality has your concepts based in one field of study dedicated to create correlation between physics characteristics of noise and the subjective reactions produced by this sound, the psychoacoustic. There are a large number of metrics, some of which are well defined and others which are not. Few have been standardized and the usefulness of a particular metric is dependant on the nature of the sound being tested.

Manufacturers who undertake sound quality testing involving the use of sound quality metrics often develop their own metrics. The choice of which sound quality metrics to apply is specific to individual purpose. Individual metrics do not give an indication of the sound quality as a whole and indeed for many appliances no metrics may currently exist to adequately quantify the subjective impression. Recent work [1, 2] has demonstrated that these measures are largely independent of the meaning of a sound so could never stand alone to define sound quality. This is because sound quality is usually defined using the principle of 'how well the sound of a product matches the user's expectations.

The procedure usually adopted over the years for considering the subjective response of people to products noise has been the A-weighting scale which was derived from the equal loudness contour curves. Its implementation is found in most sound measuring equipments and analysers and it consists in the application of the frequency response function to the acquired signal. The weighting functions act on the signal spectrum on an energy basis only. Several other aspects of the frequency contents and details in the time history of a signal must be taken into account for a more precise subjective assessment [3]. One may therefore state that from the subjective assessment point of view the A-weighting function represents a first order approximation.

Equal loudness contour curves indicate different slope rates with frequency for different sound pressure levels. For instance, the C-weighting function derived from the 100 Phon loudness curve varies less with frequency compared to the A-weighting function, which was derived from the 40 Phon curve, located in the lower amplitude range. This amplitude effects are considered in loudness calculation by the Zwicker method, as used in this work. It considers also masking effects produced by higher noise levels in some bands upon levels of adjacent bands [4].

Fluctuation strength represents the effects caused by low frequency (less than 20Hz) amplitude modulations. Roughness represents also amplitude modulation effects, with maximum sensation when modulation frequency is about 70Hz. Sharpness considers the high frequency contents of the signal, in the kHz region [4, 5].

### 3. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANNs) are algorithmic systems implemented in either software or hardware. The concept of ANNs was inspired by the way the biological brain processes information. ANNs, like people, learn by example. Learning in the biological brain occurs in a network of neurons, which are interconnected by axons. A point of contact (actually most often a narrow gap) between an axon from one neuron to another is called a synapse. Learning is a matter of adjusting the electro-chemical connectivity across these synapses.

An ANN is a network of neurons or Processing Elements (PEs) and weighted connections. The connections correspond to axons and the weights to synapses in the biological brain. A PE performs two functions. It sums the inputs from several incoming connections and then applies a transfer function to the sum. The resulting value is propagated through outgoing connections to other PEs. Typically these PEs are arranged in layers; with the input layer receiving inputs from the real world and each succeeding layer receiving weighted outputs from the preceding layer as its input. Hence the creation of a feed forward ANN, where each input is fed forward to its succeeding layer. The first and last layers in this ANN configuration are typically referred to as input and output layers. (Input layer PEs are not true PEs in that they do not perform a computation on the input.) Any layers between the input and output layers are called hidden layers because they do not have contact with any real world input or output data.

Back propagation is one of several possible learning rules to adjust the connection weights during learning by example. Learning occurs when the network weights are adjusted as a function of the error found in the output of the network. The error is the difference between the expected output and the actual output. The weights are adjusted backwards (back-propagated) through the ANN network until the error is minimized for a set of training data.

A trained ANN, i.e., a network that has learned by example, can be applied to real world problems of considerable complexity. Their most important advantage is in the ability to process data that are too complex for conventional technologies, problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be found. In general, because of their abstraction from the biological brain, ANNs are well suited for problems that people are good at solving, but for which computers are not. This class of problems includes pattern recognition and forecasting or recognizing trends in data. ANNs have been applied successfully to hundreds of applications.

### 4. JURY ANALYSIS

The methodology, the test room, the signal recordings, the reproduction and the procedure to select a jury, are presented by Nunes [6]. The jury analysis consist to compare 92 sounds, one by one, with one reference sound and to classify each sound in one of three groups. These three groups are: more pleasant than the reference, similar to reference or more unpleasant than the reference sound. The table presented to jury is showed in the Figure 1. The sounds are presented according the follow sequence:

Reference Sound Compressor sound 1
<i>Pause: one second</i>
Reference Sound Compressor sound 2
<i>Pause: one second</i>
Reference Sound Compressor sound 3
:
:

	More Pleasant	Similar	More Unpleasant
1	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
2	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
3	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
4	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
5	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
6	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
7	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
8	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
9	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
:	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
89	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
90	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
91	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
92	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Figure 1 – Table presented to jury to classify the signals

The Table 1 presents the jury analysis result. The results represents the average approval by 26 member of the jury and it was utilized to elaborate the database to training of the artificial neural network.

<i>Class</i>	<i>N° of sounds</i>
Sounds more pleasants than the reference	31
Sounds similar to the reference	30
Sound more unpleasants than the reference	31

Table 1 – Results from jury analysis

## 5. NEURAL NETWORK APPLICATION

To evaluate, elaborate and to configure the neural network it was utilized in this paper as a computational tool, the program Weka (Waikato Environment for Knowledge Analysis), a freeware software developed by Waikato University, New Zealand.

Before to get a proper configuration to the neural network it is necessary to compose the database. Starting from the noise signal in the time domain, it is necessary to take two ways: one of them classify the signal by the subjective point of view (jury analysis), while the other way represent the sound by objectives values, for example dB(A) ponderation. At the final these two information from the signal are coupled in one table to create the database. The Figure 2 shows the procedure to build the database. Once getting a appropriated database it is necessary to select a suitable neural network structure and a proper learning algorithm. By many reasons [7], the multilayer perceptron structure and backpropagation learning algorithm were choose to solve this problem.

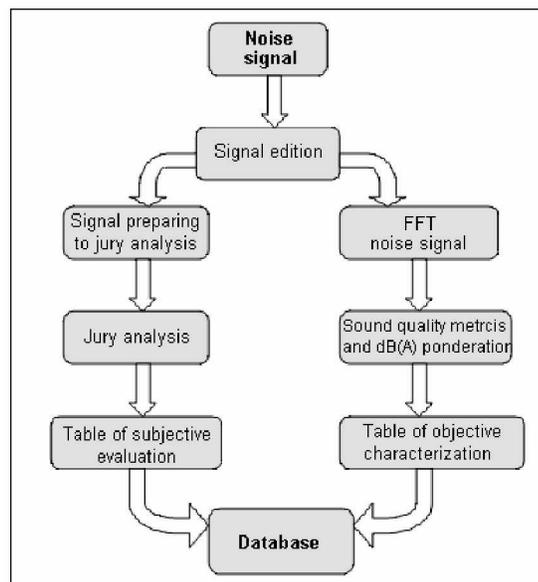


Figure 2 – Flow chart to elaborate the database

After establish the optimal point to stop the training [8] the final configuration of the neural network is trained to represent the jury opinion about that group of sounds. The configuration and the results are presented bellow:

- Neural network structure: Multilayer perceptron;
- Number of layers: 2 layers with 18 neurons to each layer;
- Momentum: 0,1
- Coefficient rate: 0,1
- Average error: 8,7 %

The Figure 3 shows a example of classification from the trained neural network. It is showing that the dB(A) ponderation is a good parameter when correlated with the jury opinion but otherwise, the sharpness values do not have any correlation with the jury opinion.

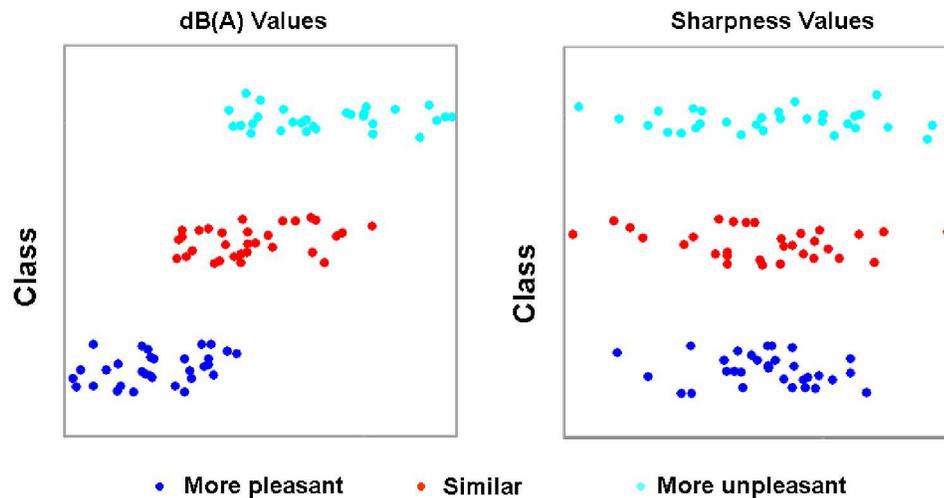


Figure 3 – Examples of results from the neural network classification

## 6. CONCLUSIONS

As presented in this work, a simple artificial neural network configuration, the multilayer perceptron, can be used to represent a jury analysis. The main point of this application is related with the database construction. It has a direct correlation to the subjective evaluation and also needs a numberless samples, by this reason the database elaboration process becomes a expensive work.

The neural network application as a classifier tool in the sound quality evaluation shows a great potential, getting expressive results even with a small quantity of samples used in the training process. An important characteristic of learning rule, based on the Hebb's postulate [7] "If two neurons on either side of a synapse are activated asynchronously, then that synapse is weakened or eliminated" make possible to use the neural networks not only as a classifier but also as a unimportant parameters identifier, it means, the neurons or attributes that has your connections weakened or eliminated, prove to be unnecessary or inconsistent values to correlate the samples. This characteristic allowed to identify loudness and dB(A) values as a representative values of subjective evaluation presented in the jury analysis.

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