A NEURAL NETWORK APPROACH TO ESTIMATE SOUND POWER LEVELS GENERATED BY ELECTRIC MOTORS

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Abstract. *In acoustic sciences electric motors are treated as negligible noise sources. In fact, a well maintained electric motor does not generate significant sound power levels by itself. However, standard industrial plants that need several electric motors to run other devices or mechanisms usually group these electric motors close to each other. That generally makes the sum of its noises become very significant, despite of the low noise caused by a single motor. That's why studying the acoustics in electric motors and, the prediction of the noise generated by these machines to prevent acoustic problems before they can cause problem to the industrial environment is important. In this study a new model to estimate sound power levels was created (through surfaces of response and neural network) using a data bank provided by the Laboratory of Acoustics and Vibration of the Federal University of Uberlândia. To check the accuracy of this new model, it was compared with existent models created by well-known authors in acoustics and with random experimental data from another data bank, not used in the conception of the new model. The new model was considered successful, since the errors of the sound power levels estimated in relation to the experimental sound power levels data were not significant.*

Keywords: *Neural Network, Response Surface, Electric Motor, Acoustic, Analytic Method.*

1. INTRODUCTION

Most of authors in acoustics area treat electric motors like negligible noise-sources, because the noise generated by one single electric motor (without mechanical problems such as unbalancing or missing lubrification) does not affect the total sound pressure levels around itself. Sound power levels upcoming from electric motors are actually small, when compared with another common sources of noise (standard machinery) in an oil refinery, for example. In this case, ovens, compressors, some types of valves in pipe net and combustion engines, are just some of the noise sources much more significant than electric motors. However, thinking about this same case, electric motors use to be grouped in specific areas in large numbers by making the maintenance, repair and overhaul of this components easier, but, this habit also make the noise of electric motors much more important, once they are grouped and their sound power levels are summed. Although the sound power level sum is a logarithmic method (which means that two identical sources of noise working together make only a 3 dB higher sound power level than one of these sources), 4 electric motors each one with sound power levels of 80 dB will create a sound pressure level field of 86 dB at 1 meter of distance, exceeding the 85 dB limit stated to a 8 hour work journey, according to Gerges (2000).So, this is the reason to study noise created by electric motors and ways to minimize its impact in human health at workplace.

According to Gerges (2000), electric motors are complex noise generator sources though the vibration of their components and the turbulent air flux at their refrigeration. So, are complex to the analytic methods to estimate the noise in this kind of motors. The complexity in the noise source identification of electric motors is also exposed by Duarte (1985). In his work the sources noise were defined as T.E.F.C. (totally enclosed fan cooled, class of all motors analyzed in this work) electric motors: the bearing, the external fan, the external fan cover and the internal fan. All of their components were parts of a complex air flow system what make the noise generation inside the motor almost impossible to analyze.

In this article, new equations are proposed to predict sound power levels of electric motors in function of its electrical power and axis rotation. These equations will be estimated by using response surfaces and a neural network (using the commercial software *MATLAB*®). The neural network will be trained by the Levenberg-Marquardt algorithm.

2. METHODOLOGY

To validate the neural network approach and analyze its accuracy, three different sound power levels were experimented: a new model generated by response surface method (RSM), the model used to electric motors shown in Bies and Hansen (2003) and the experimental data collected in an industrial plant.

The data bank was divided into two groups: a large group of motors, used to train the neural network and find the model of the RSM methodology, and another small group, used to check the accuracy of the models.

2.1. Response Surfaces

The Response Surface Method (RSM) was created by George Edward Pelham Box in the 50's and consists in to analyze the influence of a group of variables, in some response variables, and since them has been uses with great success in modeling various industrial process (Barros Neto *et. al.*, 2001). Consists of planning and analysis of experiments, which seeks to relate levels of responses with the quantitative factors that affect theses responses (Box and Draper, 1987).

At first, Box suggested the RSM applied to a second-degree equation, intending to optimize the parameters targeting a wanted response. To determine a first-degree polynomial model the common approach consists in using a factorial designed experiment, such as 2^2 factorial design or 2^3 factorial design. The design 2^2 (or 2x2, where each factor has two levels surrounding, in a tetrahedron, a center-point of the analyzed part) shown in Fig. 1 was the chosen factorial design to estimate the response surface.

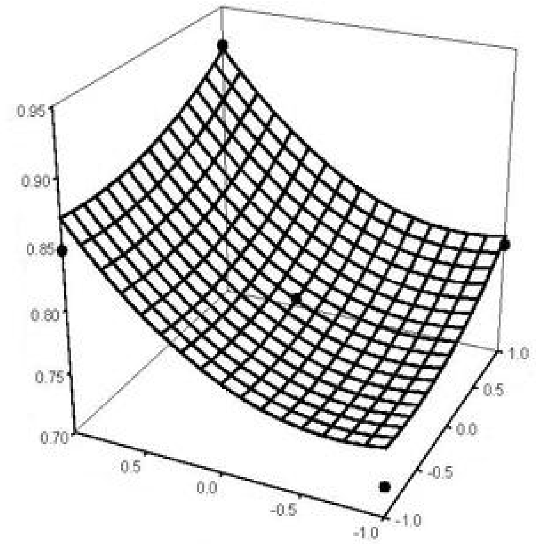

Figure 1. An example of 2^2 experiment design with equivalent response surface

The most extensive applications of RSM are in the industrial world, particularly in situations where several input variables potentially influence some performance measure or quality characteristic of the product or process (Myers and Montgomery, 2002). The case approached consists in two parameters (electric power and axis rotation) which contribution for the function (sound power level) will be determined by the RSM, working alike a multiple linear regression. The optimization does not make sense to the work's objective, once it only could bring higher or lower sound power levels optimizing the electric power and axis rotation values.

Once sound power levels use a logarithmic scale (dB) the variables of the equation should be in the same scale, so, the form of the equation that the RSM will return is presented in Eq. (1).

$$NWS = A * \log_{10}(CV) + B * \log_{10}(RPM) + C \quad [dB] \tag{1}$$

Where:

NWS is the sound power level of the electric motor (in dB), CV is the electric power of the motor (in cv), RPM is the rotation of its axis (in rpm). A, B and C are constants. A and B represent the contribution of electric power of the motor and the contribution of axis rotation of the motor to its generated sound power level respectively and C is an adjusting coefficient.

The RSM methodology was used to find the constant values: A, B and C.

2.3. Neural Networks

Artificial neural networks, which are referred to as neural network, connections, adaptive networks, neurocomputers and parallel distribution processors, are massively parallel interconnected network of simple elements intended to interact with the real world in the same way as biological nervous systems. They have been used to solve a wide variety of science and engineering problems that involve extracting useful information from complex or uncertain data (Jalel *et. al.*, 1991).

Neural networks are defined by three characteristics: architecture, training algorithm and activation function. The term comes from their similarity with the neural system present in neural biology. The activation function is the relation between input and output of the neurons (A_1, A_2, A_3 and B on Fig. 2) the architecture is defined by the connections between these neurons (f_1, f_2 and f_3 on Fig. 2) and the training algorithm is used to determine the architecture.

Basically, the training algorithm will fit the best functions (connections) between the nodes (or neurons) using previously existent data (experimental data in the majority of experiments) in order to train the neural network to give a certain output, according to random inputted value(s).

Each neuron or node, after submit its input to the activation function can send this activation to several other neurons, but this value is the same for all these synapses. What will define the difference over the irradiated neuron signals are the connections (functions determined by the architecture) between this neuron and the others that take its signal as input.

In this work the neural network used was a common ANN (Artificial Neural Network) given by the commercial software *MATLAB®* which design is not known, but trained by the Levenberg-Marquardt algorithm. Once this work does not aim a deep study of neural networks, but only their efficiency to the approached case, the neural network is used like a common black box computational tool and no further information about it is needed.

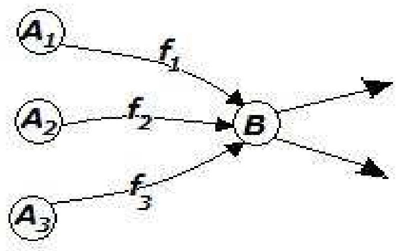

Figure 2. Schematic representation of a basic neural network

2.4. The Bies and Hansen Method

The method suggested to estimate sound power levels in electric motors in Hansen and Bies (2003) consists of two different equations, Eq.(2) to estimate sound pressure levels of motors which electric power are below 54.35 cv and Eq.(3) to estimate sound pressure levels of motors above 54.35 cv. Once the equations estimate sound pressure levels at one meter distant from the source, Eq.(4) was used to convert these sound pressure levels into sound power levels of the source.

$$L_p = 17 + 17 \log_{10}[0.736 * (CV)] + 15 \log_{10}(RPM) \quad [dB] \tag{2}$$

$$L_p = 28 + 10 \log_{10}[0.736 * (CV)] + 15 \log_{10}(RPM) \quad [dB] \tag{3}$$

$$NWS = L_p + 11 - 10 \log_{10}(D) \quad [dB] \tag{4}$$

Where:

L_p is the sound pressure level (in dB) of a noise source and D is the directivity according to the placement of this noise source.

The directivity D is defined by the installation's position of the electric motor in relation to nearby barriers and its value is shown in Fig. 3.

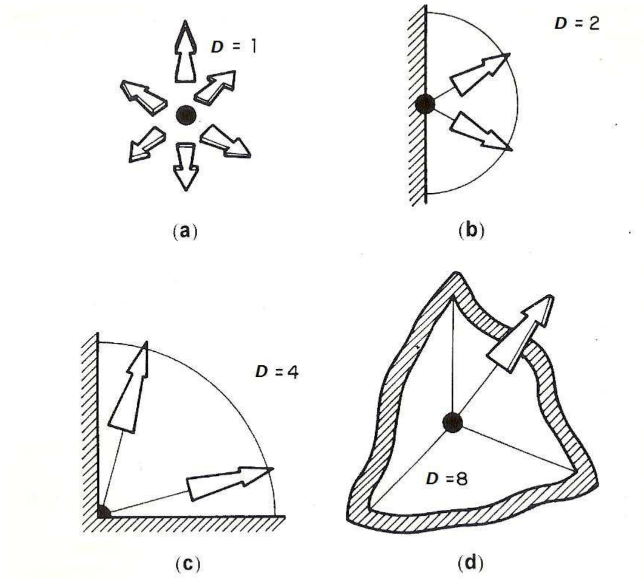

Figure 3. Directivity of noise source according to nearby barriers

The model shown in Bies and Hansen (2003) was chosen among well-known models because it is the one which presents the lowest errors to estimate sound power levels generated by an electric motor according to Mateus *et al.* (2008).

3. RESULTS

The first stance data analysis using the RSM resulted in an general equation, Eq.(5), for all the electric motors in the data bank, but the estimated sound power levels carried out unsatisfactory error levels. Following the common sense among authors of most famous acoustic books, the data was classified by electric power band, since the noise sensitivity to electric power is not linear and the adoption of electric power bands is a practical way to avoid errors originated by a single equation applied in a large parameter range data bank.

Equation (5) brings the sound power level equation to electric motors with any electric power:

$$NWS = 3.04 * \log_{10}(CV) + 6.91 * \log_{10}(RPM) + 71.47 + X \quad [dB] \tag{5}$$

Where X is a coefficient used to change the *NWS* into octave-band sound power level, shown on Tab. 1.

Table 1. X values to adjust *NWS* from Eq. (5) to octave-band sound power levels

Octave-Band Adjust Coefficients							
63 Hz	**125 Hz**	**250 Hz**	**500 Hz**	**1 kHz**	**2 kHz**	**4 kHz**	**8 kHz**
-37.39	-24.95	-14.52	-6.75	-4.84	-6.30	-10.73	-17.26

The sound power levels obtained using the Eq. (5) can be seen in Tab. 2.

Since the errors from Eq. (5) in comparison with the experimental data were not satisfactory, as can be seen in Fig. 4, the power band division of the electric motors in data bank was adopted and three new equations were obtained: Eq. (6), Eq. (7) and Eq. (8).

Table 2. Sound power levels estimated by a Eq. (5) from the RSM for all electric motors

CV	*RPM*	63 Hz	125 Hz	250 Hz	500 Hz	1 kHz	2 kHz	4 kHz	8 kHz	*NWS*
7.5	3530	61.26	73.69	84.12	91.90	93.81	92.34	87.92	81.39	98.65
20	3530	62.55	74.99	85.42	93.19	95.10	93.64	89.21	82.68	99.94
40	1780	61.41	73.85	84.28	92.05	93.97	92.50	88.07	81.54	98.80
50	3550	63.78	76.21	86.65	94.42	96.33	94.86	90.44	83.91	101.17
125	3560	65.00	77.43	87.86	95.64	97.55	96.08	91.66	85.13	102.39
200	3520	65.58	78.02	88.45	96.22	98.14	96.67	92.24	85.72	102.97
300	3580	66.17	78.60	89.04	96.81	98.72	97.25	92.83	86.30	103.56

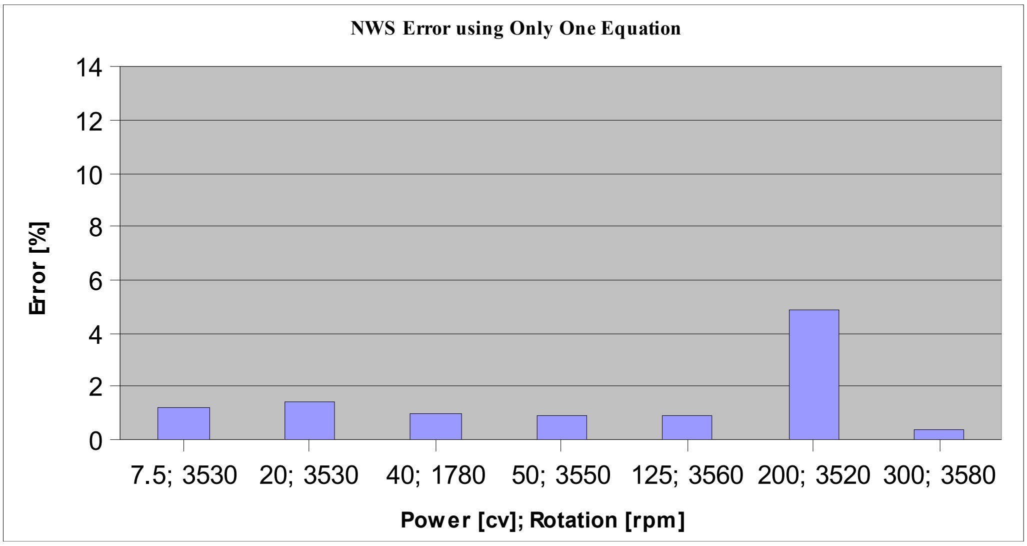

Figure 4. Error between *NWS* estimated by Eq. (5) and sound power levels identified *in situ.*

As the *X,* the coefficient value seen in Eq. (5), the X_1, X_2 and X_3 values represent, the one octave-band adjusting coefficients for Eq. (6), Eq. (7) and Eq. (8), respectively.

Equation (6) refer to electric motors with power between 1 cv and 49 cv, Eq. (8) to electric motors with power between 50 cv and 149 cv and Eq. (8) to electric motors of 150 cv and above.

$$NWS = 6.17 * \log_{10}(CV) + 7.94 * \log_{10}(RPM) + 63.46 + X_1 \quad [dB] \ \{1\ cv\ \ up\ to\ 49\ cv\} \tag{6}$$

$$NWS = 1.5 * \log_{10}(CV) + 10 * \log_{10}(RPM) + 64.55 + X_2 \quad [dB] \ \{50\ cv\ \ up\ to\ 149\ cv\} \tag{7}$$

$$NWS = 4.4 * \log_{10}(CV) + 367.4 * \log_{10}(RPM) - 1213.4 + X_3 \quad [dB] \ \{149\ cv\ \ and\ above\} \tag{8}$$

Table 3. X_1 , X_2 and X_3 values to adjust *NWS* in Eq. (6), Eq. (7) and Eq. (8) to one octave-band sound power levels

	Octave-Band Adjust Coefficients							
	63 Hz	**125 Hz**	**250 Hz**	**500 Hz**	**1 kHz**	**2 kHz**	**4 kHz**	**8 kHz**
X_1	-38.23	-26.19	-15.78	-6.85	-4.77	-5.98	-10.11	-16.89
X_2	-36.7	-23.53	-12.88	-6.14	-4.62	-6.59	-11.69	-18.03
X_3	-36.90	-24.91	-14.94	-8.53	-6.18	-7.31	-11.06	-17.18

The sound power levels obtained using the RSM with electric power divided in bands can be seen in Tab. 4.

Table 4. Sound power levels estimated by Eq.(6), Eq.(7) and Eq.(8)

CV	*RPM*	63 Hz	125 Hz	250 Hz	500 Hz	1 kHz	2 kHz	4 kHz	8 kHz	*NWS*
7.5	3530	58.80	70.83	81.24	90.18	92.26	91.05	86.92	80.13	97.03
20	3530	61.43	73.46	83.87	92.81	94.88	93.68	89.55	82.76	99.66
40	1780	60.93	72.96	83.37	92.31	94.38	93.17	89.05	82.26	99.15
50	3550	65.90	79.07	89.72	96.46	97.98	96.01	90.91	84.57	102.60
125	3560	66.51	79.68	90.33	97.07	98.59	96.62	91.52	85.18	103.21
200	3520	62.82	74.82	84.79	91.20	93.54	92.42	88.67	82.54	99.72
300	3580	66.30	78.29	88.26	94.67	97.01	95.89	92.14	86.01	103.20

The NWS values shown in Tab. 4, which errors compared with experimental values of NWS, are presented in Fig. 5.

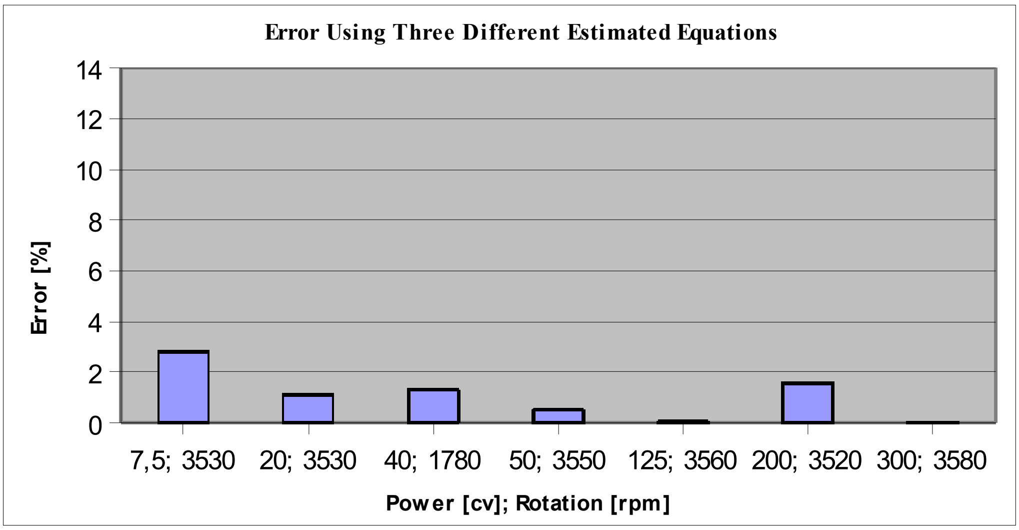

Figure 5. Error between *NWS* estimated by Eq.(6), Eq.(7) and Eq.(8) and sound power levels identified *in situ.*

The *NWS* obtained using the trained neural network can be seen in Tab. 5.

Table 5. Sound power levels estimated by the trained neural network

CV	RPM	63 Hz	125 Hz	250 Hz	500 Hz	1 kHz	2 kHz	4 kHz	8 kHz	NWS
7.5	3530	59.53	71.14	80.64	90.47	92.55	92.33	88.47	81.1	97.79
20	3530	60.71	72.24	83.01	92.33	94.59	93.53	89.28	82.45	99.29
40	1780	62.33	75.37	85.44	92.89	92.79	91.22	87	80.66	98.17
50	3550	63.45	75.3	87.62	95.72	98.48	96.05	91	84.97	102.34
125	3560	63.76	73.27	86.85	94.89	96.83	95.83	91.74	86.27	101.5
200	3520	63.95	73.11	86.03	93.98	95.74	95.64	91.89	86.27	100.96
300	3580	66.44	78.83	87.79	94.45	97.4	97.34	92.57	85.97	102.75

The NWS values shown in Tab. 5, which errors compared with experimental values of NWS, are presented in Fig. 6.

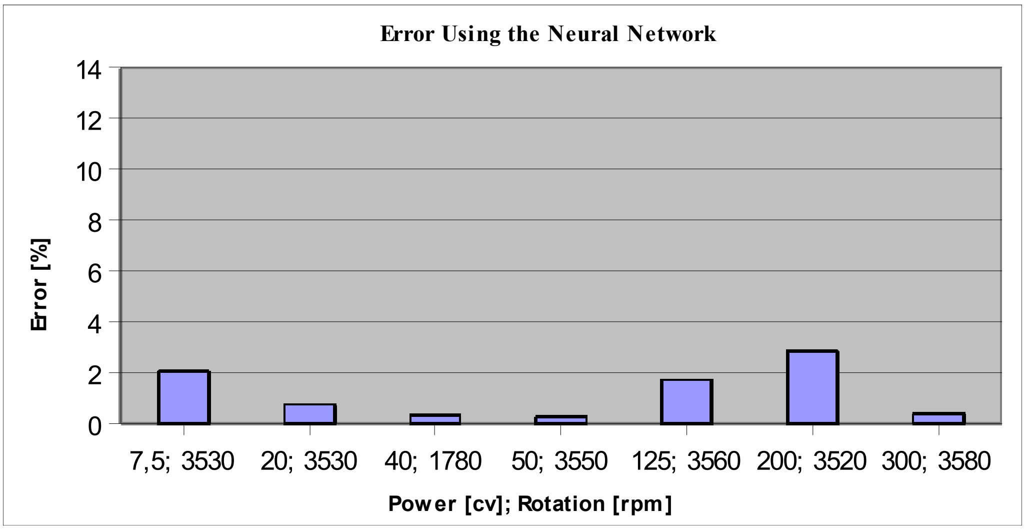

Figure 6. Error between *NWS* estimated by the trained neural network and sound power levels identified *in situ.*

In the same way the *NWS* obtained using the Bies and Hansen method can be seen in Tab. 6. The directivity *D* adopted to convert L_p to *NWS* was 2, for all the electric motors, since they were all placed in the ground with more than one meter away from any obstacle/barrier.

Table 6. Sound power levels estimated by the Bies and Hansen method

CV	*RPM*	63 Hz	125 Hz	250 Hz	500 Hz	1 kHz	2 kHz	4 kHz	8 kHz	*NWS*
7.5	3530	76.81	79.81	81.81	84.81	84.81	83.81	78.81	70.81	90.90
20	3530	84.06	87.06	89.06	92.06	92.06	91.06	86.06	78.06	98.14
40	1780	84.71	87.71	89.71	92.71	92.71	91.71	86.71	78.71	98.80
50	3550	90.86	93.86	95.86	98.86	98.86	97.86	92.86	84.86	104.94
125	3560	94.90	97.90	99.90	102.90	102.90	101.90	96.90	88.90	108.98
200	3520	96.86	99.86	101.86	104.86	104.86	103.86	98.86	90.86	110.95
300	3580	98.73	101.73	103.73	106.73	106.73	105.73	100.73	92.73	112.82

The NWS values shown in Tab. 6, which errors compared with experimental values of NWS, are presented in Fig. 7.

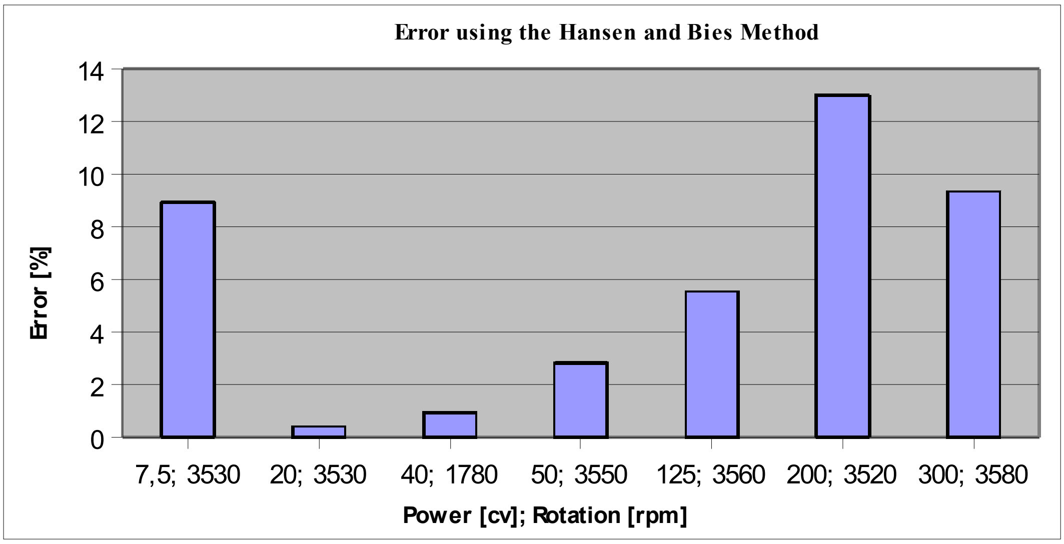

Figure 7. Error between *NWS* estimated by the Bies and Hansen method and *NWS* identified *in situ.*

4. RESULTS ANALYSIS

To condense the results the methods used are plot in Fig. 8. The last group of four columns indicates the average error. The method of Hansen and Bies does not brought the best accuracy to estimate the sound power levels of the seven random-chosen electric motors, regardless of its considered better performance among well-known methods.

All the other methods presented average error below 2%.

The RSM with Eq. (5) presented an average error around 1.5%, but with three equations (Eq. (6), Eq. (7) and Eq. (8)), showed a decreased value of the average error around 1.1%.

The propose methodology using neural networks gave an average error around 1.2%. Although the average value being a little bit higher than the RSM method (with three equations) there are some promising aspects to be investigated in the neural network method.

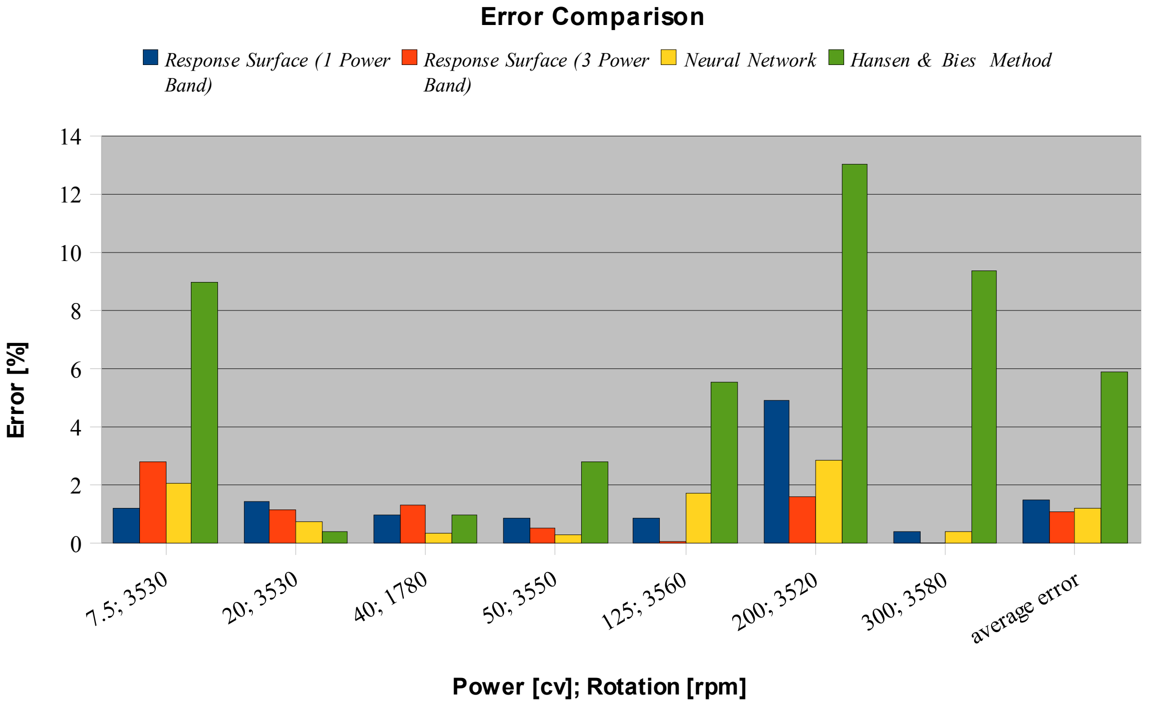

Figure 8. Error comparison for analytic and numerical methods presented in this work

5. CONCLUSION

In the end, could be noticed that the neural network was a more than satisfactory approach to estimate sound power levels of electric motors, but, it demands a substantial data bank (the one used in this work contains about 70 different electric motors) to keep its accuracy and computational process which can enhance its use.

The equations provided by the RSM also showed low deviation levels and the proposed group of equations Eq. (6), Eq. (7) and Eq. (8) presented the best accuracy of all methods with the minor average error even when compared with the famous method of Hansen and Bies (2003).

Thus we have room for future studies of new analytical acoustic equations to evaluate the noise generated by other kinds of machinery.

6. ACKNOWLEDGEMENTS

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