MODELING OF A CALIBRATION CURVE OF AN EXTERNAL AERODYNAMIC BALANCE USING MULTILAYER PERCEPTRON ARTIFICIAL NEURAL NETWORK

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Abstract. *In calibration, we seek to examine the characteristic behavior of a measuring instrument, or of a measuring system, based on comparison against a standard or reference material, which guarantees the traceability to the unity of the conventional true value. It is not always possible to perform the comparison across the entire scale, due to time and cost reasons, or to statistical fluctuations around the measured data, which makes it pointless to collect calibration data with unnecessary high resolution. For this reason, it is common practice to fit a calibration curve to interpolate the data points. One of the traditional approaches of curve fitting is the polynomial fitting by the least squares method. As an alternative to the polynomial approach, one can use Artificial Neural Networks to interpolate the calibration data set, and this is the subject of the present work. The system to be calibrated consists of the external aerodynamic balance of the subsonic wind tunnel n.º 2, the TA-2, of the Brazilian Aerospace Technical Center (CTA). The purpose of the balance is to measure the aerodynamic loads acting on the model being tested. The Multi Layer Perceptrons (MLPs) are the class of neural networks chosen in this study because the mathematical modeling of the external balance calibration is multivariate. Studies regarding the convergence of functions were carried out taking into consideration different architectures of this network class, in order to obtain adequate models for different calibration sets.*

Keywords*: Artificial Neural Network, Statistical Methods, Calibration Uncertainty, Wind Tunnel Tests, Mathematical Modeling.*

1. Introduction

In calibration, we seek to determine the characteristic behavior of a measuring instrument, or of a measuring system, based on the comparison against a standard or reference material, which carries on the traceability to the unity of the conventional true value (SENAI and INMETRO, 2000). It is not always possible to compare all the range of values of the full scale, due to time and cost, or to statistical fluctuations around the measured data. These facts make the collection of data in the full scale both impractical and unjustifiable.

For this reason, it is common practice to fit a calibration curve to the data collected during calibration, and to estimate the data points not measured though such a curve (Lira, 2002). In the case of similar quantities being related through the curve, it can be a straightforward option, but when we are dealing with different quantities, it is usual to find situations where it is required to know the class of functional relationship between the measured parameters with a significant accuracy, based on the application of the artifact under calibration. This usually happens in the calibration curve of devices such as detectors, sensors and transducers. Specific examples are the thermocouple, the photocell, the bourdon tube, strain gauges, etc.

The usual approach to perform the curve fitting is the physical (and mathematical) modeling determined by improvements in the scientific theories which involve the relationship among the relevant quantities. There is no doubt that this is the safest way to evaluate the measurement, because it is supported by scientific knowledge of cause and effect, thus giving guidance to the metrological activities. However, it can happen that the number of parameters to be considered is very large due to the occurrence of several influence quantities, making the task of physical modeling virtually impossible. In such instances it is common to recur to pure mathematical modeling as an alternative to the (unavailable) precise physical modeling, whose complexity demands a considerable theoretical knowledge of both input quantities of the measured amount and the influence quantities.

Among the traditional approaches of curve fitting, we have the polynomial method. As the polynomial fitting is a linear method in the adjustable parameters, it is possible to minimize the squared error through non-iterative computation. For a single variable system, one can solve several classes of problems by increasing the polynomial degree as needed. Nevertheless, there are multivariate systems and, for those, in addition to the question of the relationship between the measured and the related sensed quantity, it is necessary to consider the correlation among the several input quantities of the multidimensional measured amount as well. This gives rise to cross terms, involving products of input variables. Obviously, it is also possible to model polynomials in this situation combining the polynomial degrees of the input variables and the degrees of the cross terms.

Alternatively to the polynomial approach, one can use Artificial Neural Networks to interpolate the calibration data set, and this is the subject of the present work (Barbosa, 2004). Based on biological neurons, the artificial neurons network intends to be a biologically inspired modeling tool in terms of its functional principle. The architecture of interacting artificial neurons transforms a path of multiple internal signals that, obeying a coherent flux, supplies an output dependent on the input signal. It means that it is possible to create a neural structure to represent the input/output relationship based on complex mathematical models (Hertz et al, 1991).

Artificial Neural Networks can be trained to approximate a function with arbitrary level of precision. Through an iterative process, the network parameters are adjusted, and the input-output relationship is fitted to the calibration data, allowing the bounding of the error of the mathematical calibration function.

The Multilayer Perceptrons (MLPs) is the class of neural networks chosen in this study because the mathematical model of the external balance of a wind tunnel is multivariate. In our studies, we have taken into consideration the dependency among the input quantities, and experiments on the production of calibration functions were carried out where different architectures of this network class were considered. The calibration curve of the external wind tunnel balance is presented, as a practical example of the employment of MLPs. Convergence results are also presented for different sets of calibration data, corresponding to different sideslip angles.

2. The Muti Layer Perceptron Artificial Neural Network

Artificial Neural Networks (ANN) are computational intelligence techniques, which may be considered capable of resolving certain classes of problems, among them the approximation of functions, sometimes called mathematical modeling. The approximation of the function may be used to fit the calibration curve (CC) taking into account the quantities related to the calibration process. The modeling in question refers to the calibration of the external balance of the Subsonic Wind Tunnel n.º 2, the TA-2. The kind of artificial network employed is the Multi Layer Perceptron (MLPs). Neural Networks have already been used in calibration curve fittings. Other kinds of ANN can be employed, such as Radial Base Functions, RBFs, Committee Machines, etc (Barbosa, 2004).

A node may represent the artificial neuron, based on the biological neuron. The node has a single output and several inputs. Each input signal is multiplied individually by a factor called "synaptic weight". One of the inputs is chosen as the unity (threshold). The results of this operation are summed, which gives rise to the weighted sum. The weighted sum is the input value of the transfer function (Hertz et al, 1991).

Figure 1 presents the architectural graph of the ANN used in this study. It has an input layer of source nodes, a hidden neuron layer and an output neuron layer. It is referred to as multilayer perceptrons (MLPs) and is said to be fully connected, as every node in each layer of the network is connected to every other node in the adjacent forward layer.

There are two modes of MLP operation, the learning process and the simulation process. In the former, the desired input/output vectors pairs are supplied to the source/output nodes of the MLP. Adjustments are applied to the synaptic weights W through the iterative learning process. The suitable values of the synaptic weights are those that decrease the index performance, known as Performance Function (PF). In the latter form of network operation, the input vectors obtained during testing are supplied to the source layer of the MLP and, from the weights W fixed during the learning phase, one obtains the values of the corresponding output vectors (Haykin, 1999).

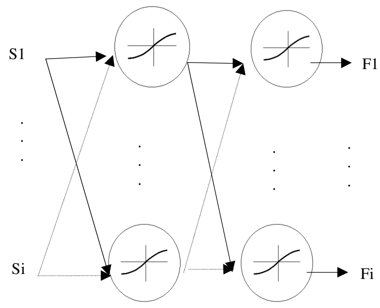

Figure 1: Architectural graph of the MLP neural network.

The conception of the MLP involves the following aspects:

– Number of layers. It may be any number, usually greater than three;
– Number of neurons in each layer. The hidden layers may have any number of neurons. The number of output variables limits the number of neurons of the output layer. In this work several three layered MLPs are employed, where the number of neurons of the hidden layer and the number of the nodes of the source layer change;
– Transfer Function (TF). It is based on the biological neuron transfer function: the sigmoid function. Equation (1) expresses the TF employed in this work;
– Learning algorithm. The learning algorithm used is the Levemberg-Maquardt method (Lira, 2002);
– Synaptic weights initialization. This parameter determines the convergence and the period of convergence of the neural network. For initialization, the value of the synaptic weights chosen is 0.0001;
– Learning performance or Performance Function (PF). The measure of learning performance is the quadratic error summation, Σe^2, which consists of the squared difference between the actual response of the neural network and the desired response, summed over the entire data set;
– Learning rate. A suitable choice of this rate avoids the trapping of the ANN in the local minimum. The value of the learning rate chosen is equal to 10;
– Iterative number. It leads to an improvement of the PF. Each iteration corresponds to the presentation of the complete set of input/output vectors pairs to the ANN. In this study, this number is 1000.

$$\varphi = \frac{2}{\left[1+\exp(-2x)\right]} - 1 \qquad (1)$$

In mathematical terms, the neurons of the MLP for each output variable F_i are described by writing the following equation:

$$F_i = \varphi_i\left(\sum_{n=1}^{N} w_{2in}\,\varphi_n\left(\sum_{m=1}^{M} w_{1nm} S_m\right)\right) \qquad (2)$$

n = 1, 2,…, ... N is the hidden layer neuron index;
m = 1, 2,…, ... M is the source layer node index;
φ_i: transfer function of the neurons of the output layer;
W_{2in}: synaptic weights of the neurons of the output layer;
φ_n: transfer function of the neurons of the hidden layer;
W_{1nm}: synaptic weights of the neurons of the hidden layer;
S_m are the input signals.

3. The External Balance Calibration

A six-component external balance is used to measure the loads F_i (i = $1,...,6$) acting on the model during the wind tunnel test at the TA-2 aerodynamic facility. F_1, F_2 and F_3 denote forces and F_4, F_5 and F_6 denote moments; the load cells of the balance provide the readings S_i (i = $1,...,6$). A balance calibration is performed prior to the tests (Reis, 2004). The calibration is accomplished by applying loads to the balance through a system of cables and pulleys. A set of approximately one hundred 10 kg weights is used to apply the calibration loads (Figure 2). Seventy-three loading combinations are used.

The values representing the loads applied originate from the application of weights on the calibration cross. The symbols F_1, F_2, F_3, F_4, F_5 and F_6 are used for the drag, side and lift forces, and the rolling, pitching and yawing moments, respectively. At the subsonic wind tunnel TA-2, a calibration performed at $\beta = 0$ (Sideslip angle) is called *alfa* calibration and *beta* calibration otherwise.

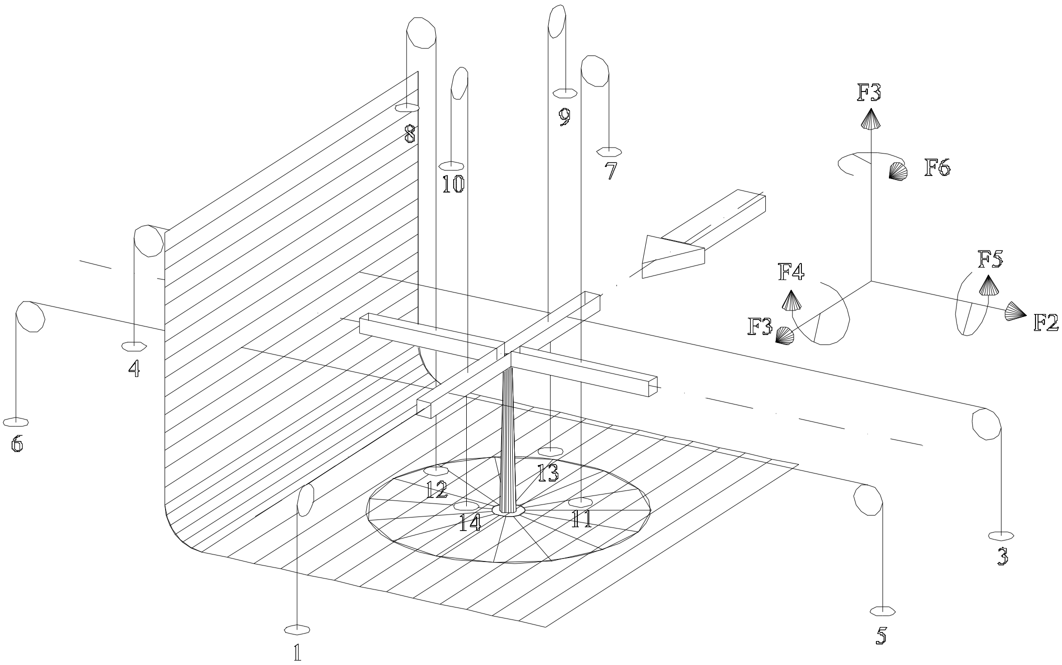

Figure 2: Loading system for balance calibration. The numbers 1,...,14 represent points of application of weights.

4. Methodology

The methodology of curve fit through the three layered MLP consists in submitting it to the learning process for several numbers of neurons in the hidden layer. The results for the different MLPs employed are compared as well as the results for MLP fit and polynomial fit.

4.1 Six inputs and six outputs

4.1.1 The polynomial fit for alfa calibration

Using the least squares method, a calibration curve is fitted to each set of 73 points $(F_i\,; S_1,S_2,S_3,S_4,S_5,S_6)_k$, $i = 1,...,6$ for an α calibration.

For the α calibration case, the fitting model is a linear combination of 27 functions of S_i which are: S_1, S_2, S_3, S_4, S_5, S_6, S_1^2, S_1S_2, S_1S_3, S_1S_4, S_1S_5, S_1S_6, S_2^2, S_2S_3, S_2S_4, S_2S_5, S_2S_6, S_3^2, S_3S_4, S_3S_5, S_3S_6, S_4^2, S_4S_5, S_4S_6, S_5^2, S_5S_6, S_6^2 . The model thus, includes twenty-seven adjustable parameters a_j ($j = 1,...,27$) for F_1, twenty-seven adjustable parameters b_j for F_2, and so on, until reaching the f_j parameters for F_6.

The matrix equation for the multivariate model (multiple inputs and outputs) is as follows:

$$\begin{bmatrix} F_1 \\ F_2 \\ F_3 \\ F_4 \\ F_5 \\ F_6 \end{bmatrix}_{6x1} = \begin{bmatrix} a_1 & a_2 & \cdots & a_{27} \\ b_1 & b_2 & \cdots & b_{27} \\ \ddots & & & \\ & \ddots & & \\ & & \ddots & \\ f_1 & f_2 & \cdots & f_{27} \end{bmatrix}_{6x27} \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_6 \\ S_1^2 \\ S_1 S_2 \\ S_1 S_3 \\ \vdots \\ S_5 S_6 \\ S_6^2 \end{bmatrix}_{27\times1} \tag{3}$$

For example, the 73 points $(F_1 ; S_1,S_2,S_3,S_4,S_5,S_6)_k$ are fitted to the model:

$$\begin{aligned} F_1(S) &= a_1S_1 + a_2S_2 + a_3S_3 + a_4S_4 + a_5S_5 + a_6S_6 + \\ & a_7S_1^2 + a_8S_1S_2 + a_9S_1S_3 + a_{10}S_1S_4 + a_{11}S_1S_5 + a_{12}S_1S_6 + \\ & a_{13}S_2^2 + a_{14}S_2S_3 + a_{15}S_2S_4 + a_{16}S_2S_5 + a_{17}S_2S_6 + a_{18}S_3^2 \\ & + a_{19}S_3S_4 + a_{20}S_3S_5 + a_{21}S_3S_6 + a_{22}S_4^2 + a_{23}S_4S_5 + \\ & a_{24}S_4S_6 + a_{25}S_5^2 + a_{26}S_5S_6 + a_{27}S_6^2 \end{aligned} \tag{4}$$

4.1.2 MLP method for alfa calibration

The MLP synaptic weights are set through the Levenberg-Maquardt learning process. This process consists of a regression based on least squares, with a linear approach around the error points (Barbosa,2004). Equation (5) presents the synaptic weights set at each iteration. Equation (6) presents the evaluation of the Jacobean matrix used.

$$\vec{w}(n+1) = \vec{w}(n) - [\vec{J}^T(n)\vec{J}(n) + \lambda\vec{I}]^{-1}\vec{J}^T(n)\vec{e}(n) \tag{5}$$

n : 1, 2,… iteration index;
$\vec{w}$: column vector of synaptic weights and thresholds;
$\vec{e}$ *:* column vector of output errors (difference between the desired and MLP output values);
$\vec{J}$: Jacobean matrix , expressed by Eq. (6).

$$\vec{J}(n) = \begin{bmatrix} \partial e1/\partial w1 & \ldots\ldots & \partial e1/\partial wm \\ . & . & . \\ . & . & . \\ \partial en/\partial w1 & \ldots\ldots & \partial en/\partial wm \end{bmatrix} \tag{6}$$

Six inputs S_{im} and six outputs F_i are used for the calibration fit in the alfa calibration case.

Figure 3 presents the Performance Function (Σe^2) values related to the amount of neurons in the hidden layer for three sideslip angles (β). The straight line corresponds to the Performance Function of the polynomial fit. The iteration number is 1000.

4.2 Sideslip angle influence

In order to analyze the traceability, after the learning process, the MLP predicts the F_i outputs, through the simulation process. The MLP will quantify the traceability.

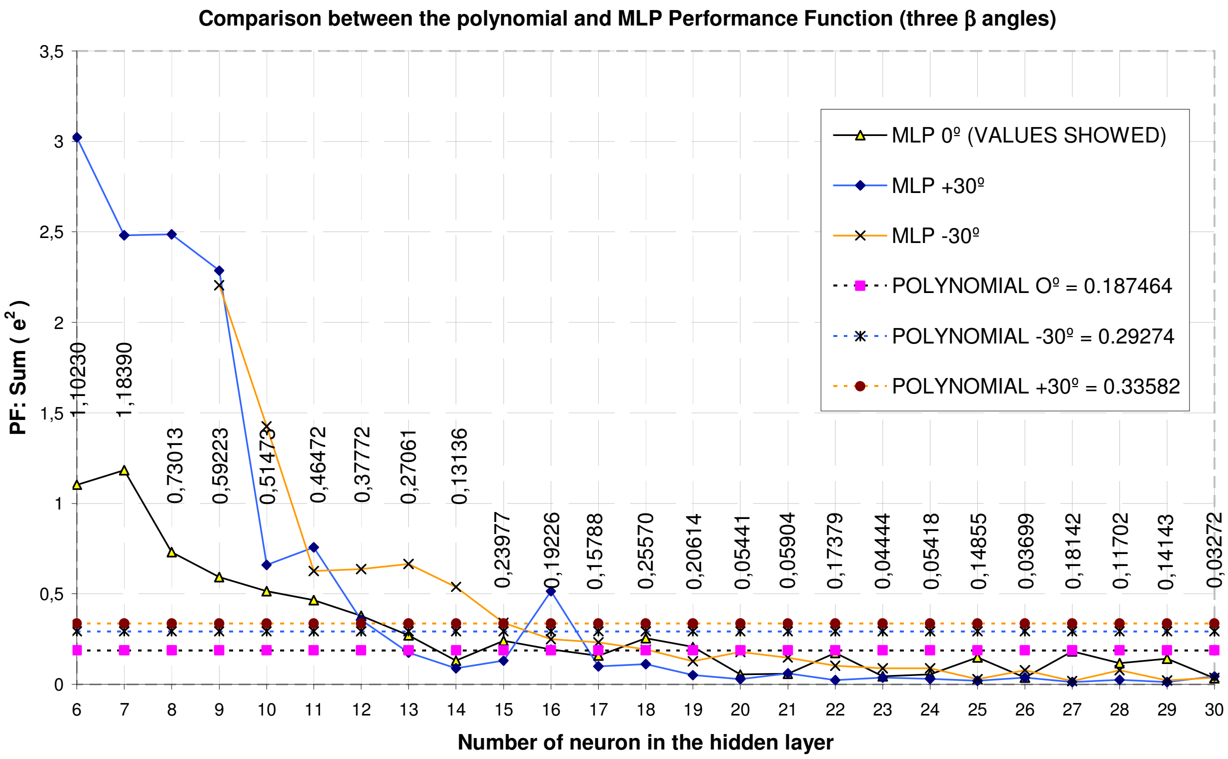

Figure 3: Performance Function for the polynomial and MLP for the learning process. Three sideslip angles (β) are considered.

4.2.1 Traceability quantification

Figure 4 shows the MLP Performance Function when one tries to predict the F_i outputs. One notes that the PF values are greater than that found for the learning process, reaching the order of 10^7. Obviously, the traceability is not suitable for the ground tests performed at the wind tunnel TA-2.

The sideslip angle is an important influence quantity and must be taken into consideration in the calibration fit of the external balance. Nevertheless, calibration in several sideslip angles is a cumbersome task and takes time and increases costs. Therefore, another learning process was carried out which included the sideslip angle as input and output.

4.2.2 The polynomial fit for beta calibration

For a β calibration, there are 219 data points and equation (4) becomes:

$$\begin{aligned}
F_1(S) &= a_1 S_1 + a_2 S_2 + a_3 S_3 + a_4 S_4 + a_5 S_5 + a_6 S_6 + \\
& a_7 S_1^2 + a_8 S_1 S_2 + a_9 S_1 S_3 + a_{10} S_1 S_4 + a_{11} S_1 S_5 + a_{12} S_1 S_6 + a_{13} S_1 \sin\beta + a_{14} S_1 \cos\beta + \\
& a_{15} S_2^2 + a_{16} S_2 S_3 + a_{17} S_2 S_4 + a_{18} S_2 S_5 + a_{19} S_2 S_6 + a_{20} S_2 \sin\beta + a_{21} S_2 \cos\beta + \\
& a_{22} S_3^2 + a_{23} S_3 S_4 + a_{24} S_3 S_5 + a_{25} S_3 S_6 + a_{26} S_3 \sin\beta + a_{27} S_3 \cos\beta + \\
& a_{28} S_4^2 + a_{29} S_4 S_5 + a_{30} S_4 S_6 + a_{31} S_4 \sin\beta + a_{32} S_4 \cos\beta + \\
& a_{33} S_5^2 + a_{34} S_5 S_6 + a_{35} S_5 \sin\beta + a_{36} S_5 \cos\beta + \\
& a_{37} S_6^2 + a_{38} S_6 \sin\beta + a_{39} S_6 \cos\beta
\end{aligned} \tag{7}$$

The matrix equation for the multiple inputs and outputs follows the structure of Eq.3, but with 39 intputs.

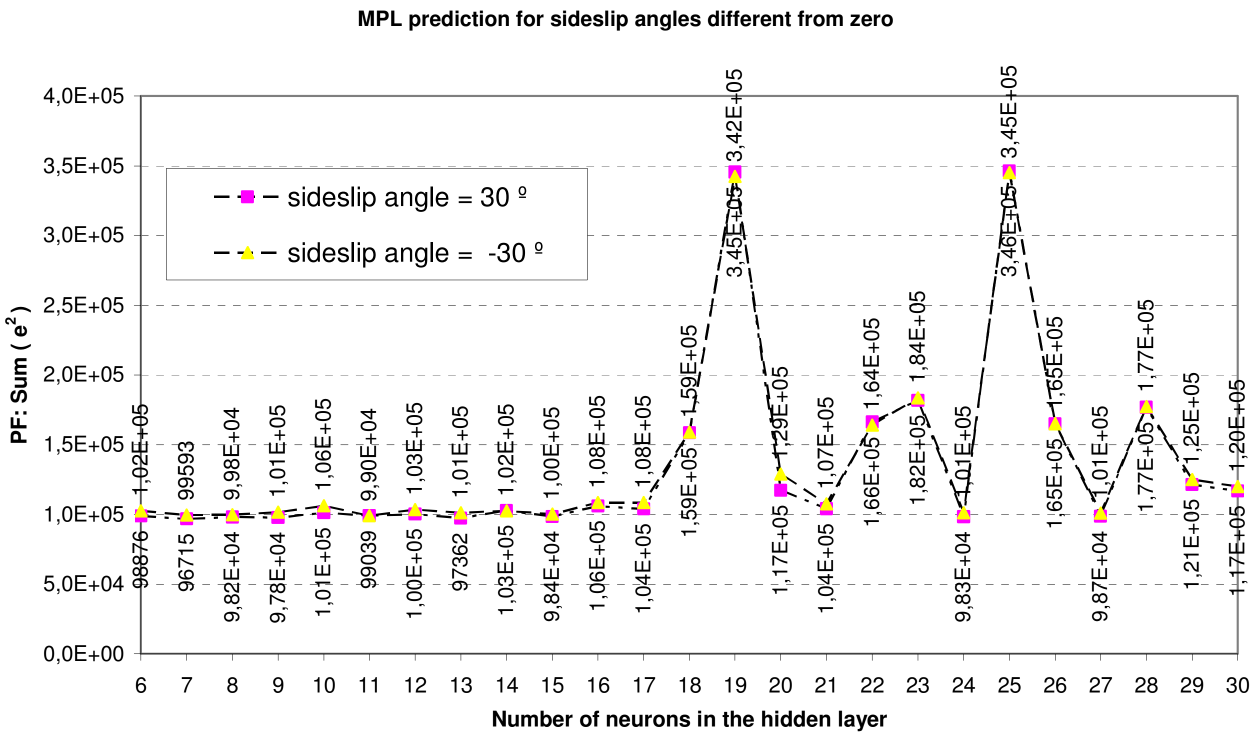

Figure 4: MLP prediction. Results for 1000 iteractions and 6 inputs/outputs.

4.2.3 MLP method for beta calibration

The learning process which considers the sideslip values is the same as described in section 4.1.2, except for the number of inputs and outputs. Six of them are the same S_m and F_i used in the alfa calibration. The 7th input and output corresponds to the angle value.

Figure 5 presents the Performance Function (Σe^2) values related to the amount of neurons in the hidden layer. The straight line corresponds to the Performance Function of the polynomial fit. The iteration number is 1000. Note that the sine and cosine functions of the sideslip angle are not presented to the MLP, but the angle itself.

5. Conclusions

The employment of the MLP provides the calibration curve fit thereby allowing the possibility of choice of the Performance Function level. When the number of neurons in the hidden layer increases, the accuracy of the MLP becomes better than that achieved by the polynomial fit employed nowadays at the wind tunnel TA-2.

In order to assess the calibration uncertainty it is necessary to establish the relationship between the quantities through a mathematical modeling (INMETRO, 2003). In the present work two mathematical modeling approaches were employed: polynomial and neural.

The former has the advantage of providing the curve fit by means of only one iteration. The disadvantage is the difficulty in modeling the suitable polynomial.

In the latter approach, the advantage is that the modeling is that imposed by the MLP. It is the MLP that solves the problem of relationship between the quantities. However, it is necessary to work on all the aspects cited in the section 4.1.2.

Another advantage of the MLP is its capacity of quantifying the influence of a quantity in a calibration process, as noted in section 4.2.1.

Using MLP the previous knowledge of the relationship between loads and angles, expressed by the sine or cosine functions is not necessary. The MLP is capable of discovering that relationship.

In recent years, the industry, in general, has sought to increase design efficiency. To achieve this propose, it is necessary to provide reliable ground testing data (ISO/IEC, 1999).

This study presents an alternative methodology to the calibration curve fit of the external balance and to the analysis of the traceability maintenance.

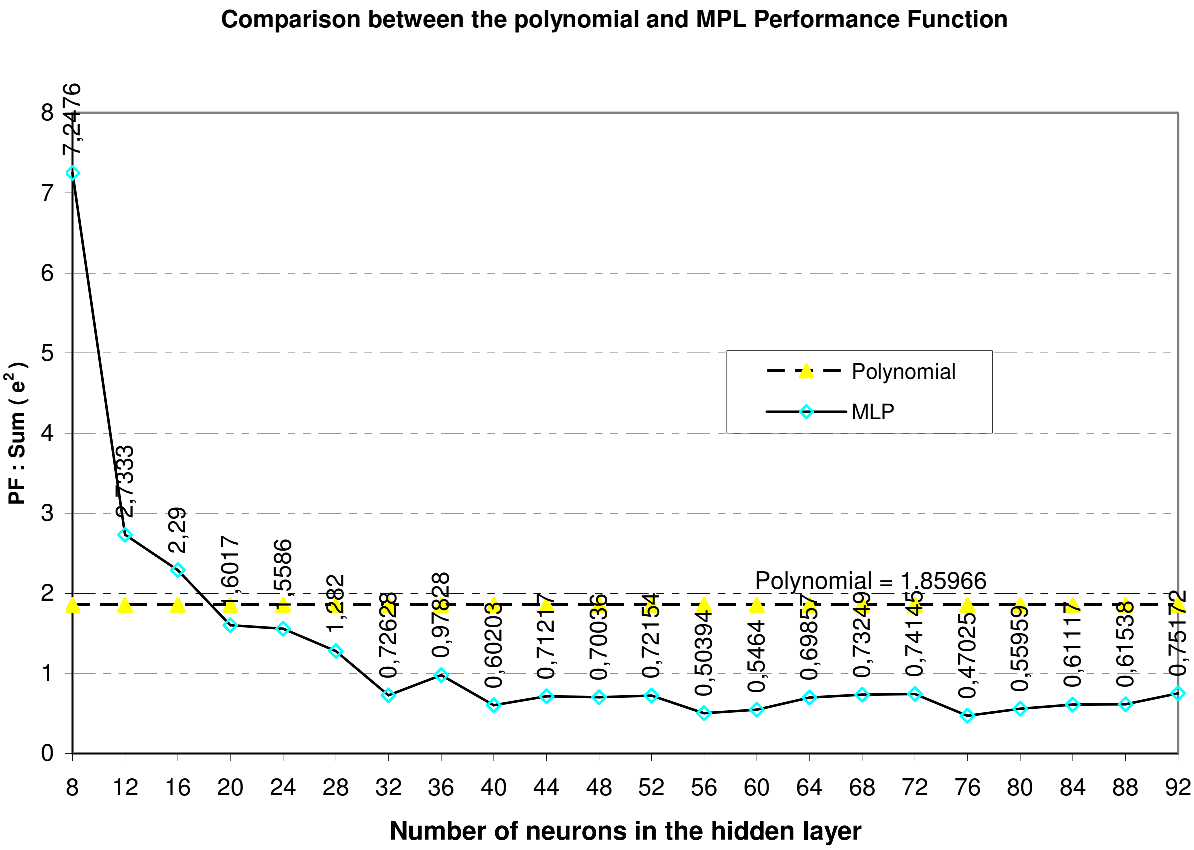

Figure 5: Performance Function for the polynomial and MLP fit, for the learning process. One of the inputs/outputs is the sideslip angle whose values are 30 º. -30 º and 0 º.

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