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MEASUREMENT UNCERTAINTY CONTRIBUTION TO THE CALIBRATION CURVE FITTING OF AN AERODYNAMIC EXTERNAL BALANCE USING MLP ARTIFICIAL NEURAL NETWORK

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Abstract: The aim of this study is to fit a calibration curve to a multivariate system. The experimental data are generated from the calibration of the aerodynamic external balance of the subsonic wind n.º 2, the TA-2, of the Brazilian Aerospace Institute, IAE. Multilayer Perceptrons (MLPs) Artificial Neural Networks are employed. To fit the calibration curve, the MLPs are submitted to the learning process. The measurement uncertainties are taken into consideration, through the modification of the MLP learning algorithm, which in its classical approach, considers the data points free from error sources. The results of both methodologies, learning algorithm endowed or without uncertainties, are compared.

Keywords: Multilayer Perceptrons, Calibration Curve, Measurement Uncertainty, Wind Tunnel, Repeatability.

1. INTRODUCTION

In modern metrology there is a great concern about uncertainty. Two international references, the ISO/IEC 17025 [1] and the ISO GUM [2] recommend the assessment of uncertainty in measurements. In general aspects, calibrations are performed in order to keep the measurement traceability. It is worth emphasizing the important role of uncertainty in the traceability definition [3]: "property of the result of a measurement or the value of a standard whereby it can be related to stated references, usually national or international standards, through an unbroken chain of comparisons all having stated uncertainties".

The Calibration Curve (CC) establishes the relationship between the input and output quantities. This relationship is sometimes nonlinear. In the case of the external balance of the TA-2 wind tunnel, the CC relates the load cell readings, whose quantity is the difference of electrical potential, with the loads applied to the balance during calibration, whose quantities are force or moments of force. The loading is performed by applying weights through a system of cables and pulleys [4] [5].

In the multivariate regression, i.e., in the learning process of the MLPs, it is unusual to take into consideration the uncertainties in the loads. In this study, the influence of the load uncertainties estimates on the MLP learning algorithm is verified.

2. EXTERNAL BALANCE CALIBRATION

A six component external balance is used to measure the loads F_i ($i = 1,\ldots,6$) 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 ($i = 1,\ldots,6$). A balance calibration is performed prior to the tests [4]. 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 (Fig. 1).

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 *alpha* calibration and *beta* calibration when otherwise. Seventy three and two hundred and nineteen loading combinations are employed for alpha and beta calibrations, respectively.

Figure 1. **Loading system for balance calibration at TA-2 facility**

Two alpha calibrations presenting the same configuration are used in this study. The first one is employed in the MLPs learning process and the other to verify the repeatability.

3. THE MULTILAYER 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 kind of artificial network employed is the Multi Layer Perceptron (MLPs). Neural Networks have already been used in calibration curve fittings [6].

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 being equal to 1 (threshold). The results of this operation are summed, which is called weighted sum. The weighted sum is the input value of the transfer function.

Figure 2 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 [7].

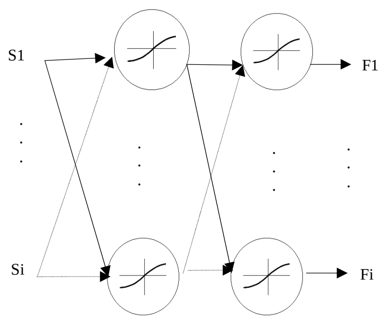

Figura 2. Architectural graph of the MLP neural network.

The conception of the MLP involves the following aspects:

– Number of layers. In this paper, this is equal to 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 study 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 study;

– Learning algorithm. The learning algorithm used is the Levemberg-Maquardt method [8]. The algorithm was modified to account for the uncertainties in the MLP output;

– 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 algorithm tries several rates for the MLP convergence. The step chosen for the learning rate increment is equal to 50;

– 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 2000.

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

In mathematical terms, the neurons of the MLP for each output variable F_i are described by 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_{1in}: synaptic weights of the neurons of the hidden layer;
S_m are the input signals.

The MLP synaptic weights are set through the Levemberg-Maquardt learning process. This process consists of a regression based on least squares, with a linear approach around the error points at the n^{th} iteration [6]. The synaptic weights are set through the matrix equation:

$$\vec{w}(n+1) = \vec{w}(n) - \left[\vec{J}^T(n)\vec{J}(n) + \lambda\vec{I}\right]^{-1}\vec{J}^T(n)\vec{e}(n) \quad (3)$$

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 Equation (4).

$$\vec{J}(n) = \begin{bmatrix} \partial e1/\partial w1 & \cdots & \partial e1/\partial wm \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \partial en/\partial w1 & \cdots & \partial en/\partial wm \end{bmatrix} \quad (4)$$

Following the traceability definition and the metrological recommendations [1] [2], data uncertainties were considered in the MLP learning algorithm.

The steps for modifying the learning algorithm for metrology best practice involve first-order Taylor series approximation of the error vector around the n^{th} iteration:

$$\vec{e} = \vec{e}(n) + \vec{J}^T(n)[\vec{w}(n+1) - \vec{w}(n)] \quad (7)$$

Minimizing the quadratic error summation considering the uncertainties (covariance matrix) is equivalent to minimizing the expression [8] [9]:

$$\vec{e}^T (u_F^2)^{-1} \vec{e} \quad (8)$$

u_F^2: Load covariance matrix

Substituting Equation (7) into Equation (8) yields:

$$\{\vec{e}(n) + \vec{J}^T(n)[\vec{w}(n+1) - \vec{w}(n)]\}^T (u_F^2)^{-1}\{\vec{e}(n) + \vec{J}^T(n)[\vec{w}(n+1) - \vec{w}(n)]\} \quad (9)$$

Differentiating Equation (9) with respect to $\Delta\vec{w} = \vec{w}(n+1) - \vec{w}(n)$ and setting the results equal to zero, gives rise to:

$$\vec{J}^T(n)(u_F^2)^{-1}[\vec{e}(n) + \vec{J}\,\Delta\vec{w}] = \vec{J}^T(n)(u_F^2)^{-1}\vec{e}(n) + J^T(n)(u_F^2)^{-1}\vec{J}(n)\,\Delta\vec{w} = 0 \quad (10)$$

Rearranging Equation (10) and inserting the learning rate λ to avoid the singularity of the inverse matrix, one finds the MLP learning equation endowed with uncertainties:

$$\vec{w}(n+1) = \vec{w}(n) - \left[\vec{J}^T(n)(u_F^2)^{-1}\vec{J}(n) + \lambda\vec{I}\right]^{-1}\vec{J}^T(n)(u_F^2)^{-1}\vec{e}(n) \quad (11)$$

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 learning Performance Functions values were compared either for the entire data set or for the individual load values. Both cases, learning endowed with or without load uncertainties are considered as well.

Besides the first calibration employed in MLP learning, a second one, performed at the same laboratorial configuration, was used to test the short-term calibration repeatability. For the second calibration, the MLP operated in the simulation mode. The input vectors, i.e., the load cell readings, are presented to the MLP source layer. Keeping the synaptic weights, the output vector values are computed in order to estimate the PFs, which correspond to the quadratic error summation. The PFs were estimated when considering and not considering the load uncertainties.

5. DISCUSSION

Figure 3 shows the PF values versus the number of neurons for the 73 loading configuration. There is, predominantly, a PF value decrease when the number of neurons in the hidden layer increases, whether the load uncertainties are considered or not.

Figure 4 presents the uncertainty profile employed in this study, which consists of the uncertainties in the estimation of the friction forces originating between cables and pulleys during the external balance calibration. The average level of the uncertainties is shown as a dotted line.

The PFs as a function of the number of neurons in the hidden layer for each load component, are shown in Figs. 5 to 10. The learning algorithm is endowed or not with load uncertainties. These figures highlight the differences between the MLP learning process with and without uncertainties. It can be seen that the quadratic error summation for the loads F_4 and F_6 are predominantly lowest for the case without load uncertainties (Figures 8 and 10). As one can note, this result is in accordance with Figure 4, which indicates uncertainties associated to loads F_4 and F_6 below the average level. For the other load components either the PFs are highest in the case of considering the uncertainties (Figures 5, 7, and 9) or the curves intersect each other (Figure 6). Once again, these results are in accordance with Figure 4, which presents load uncertainties greater than or next to the average level.

Figure 11 shows the PFs versus the number of neurons in the hidden layer, for the MLP submitted to the simulation process, with or without considering the load uncertainties. In the PF curves presented, the short-term repeatability of the external balance calibration for the entire data set can be extracted.

Seeking the best MLP architecture to estimate the calibration curve, one could choose the one which promotes the lowest PF value to represent the balance calibration repeatability. Nevertheless, this choice is not so evident, once there is not a defined minimum. Instead, the minimum value oscillates in a region between 7 and 12 neurons in the hidden layer. After this period, a tenuous PF increasing tendency occurs (Figure 11).

6. CONCLUSIONS

Recently, industry has been concerned about continuous optimization of projects. To achieve this goal, it is mandatory to provide reliable data.

In uncertainty assessment and calibration there is a necessity of establishing the mathematical relationship between the input and output quantities. The MLP has the advantage of solving the relationship between the involved quantities, since the mathematical modeling is the one imposed by the MLP architecture. However, it is necessary to work on all the aspects cited in section 3.

This study presents an alternative methodology for multivariate curve fitting and for the analysis and maintenance of traceability.

It is possible to choose the PF accuracy for the calibration curve fitting, employing MLP. The value of the quadratic error summation achieved can be negligible and therefore is suitable for even the most rigorous measurement accuracy requirements. Obviously, this situation happens at the expense of computational time, since the processing is iterative and the number of parameters in each layer is proportional to the number of neurons.

The possibility of taking into account the measurement uncertainties, without MLP convergence and computational drawbacks, has been demonstrated. The results agree with the intuition that the curve fitting for quantities associated with low uncertainties converge faster. Considering uncertainties is in accordance with metrology best practice, recommended by international standardization [1] [2] [3].

The Performance Function may be used to quantify the repeatability of successive calibrations when the MLP is employed in the simulation mode.

Calibration curve fitting employing MLP, without considering measurement uncertainties may over or underestimate the Performance Function, as discussed in section 5.

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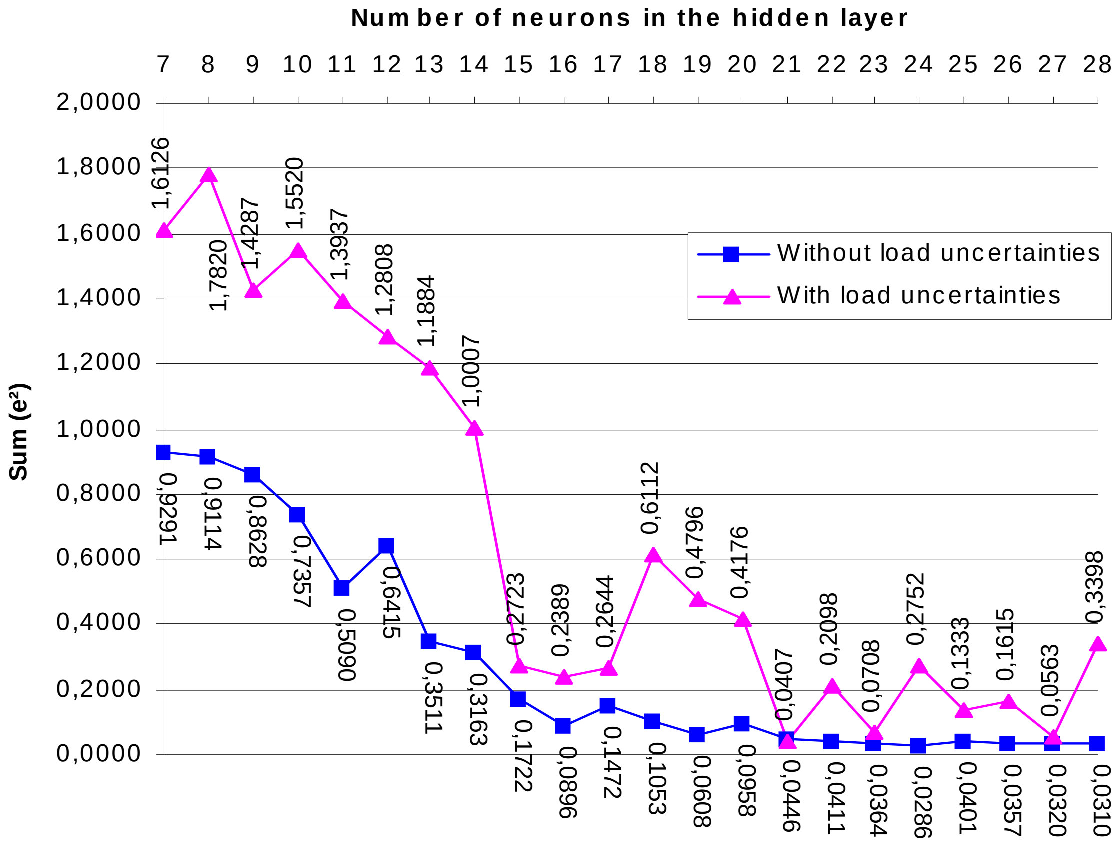

Figure 3 – MLP Performance Function for the learning mode.

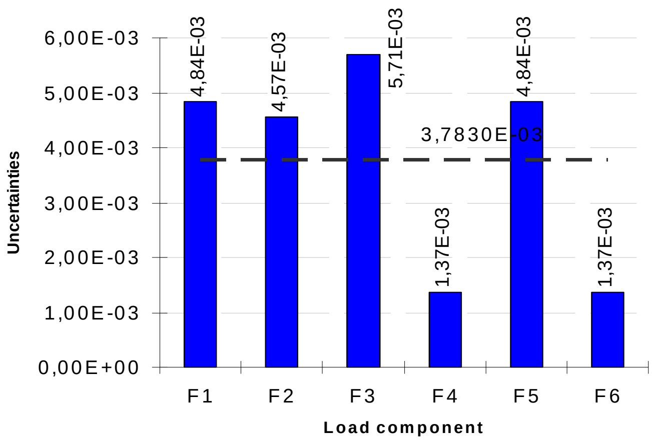

Figure 4 – Loads uncertainties and average level.

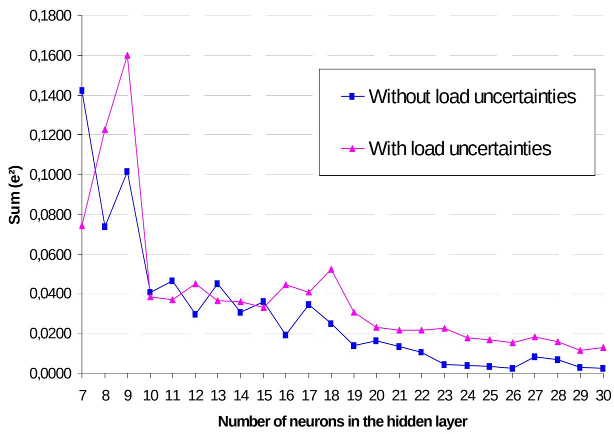

Figure 5 – Learning Mode Performance Functions for F_1.

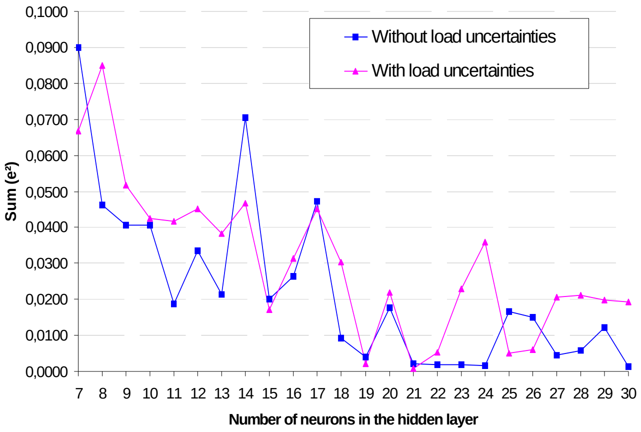

Figure 6 – Learning Mode Performance Functions for F_2.

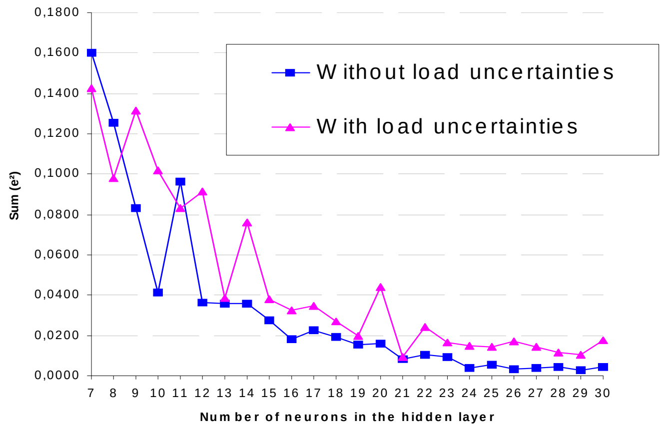

Figure 9 – Learning Mode Performance Functions for F_5.

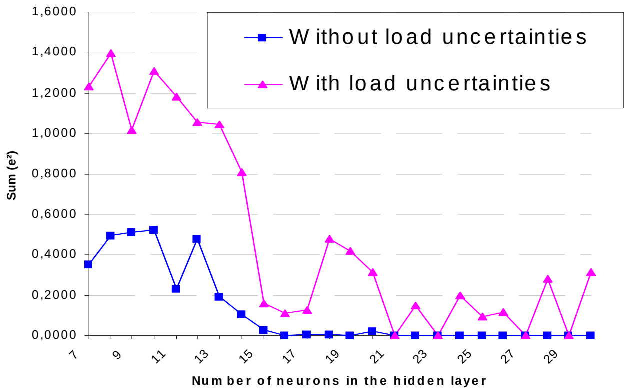

Figure 7 – Learning Mode Performance Functions for F_3.

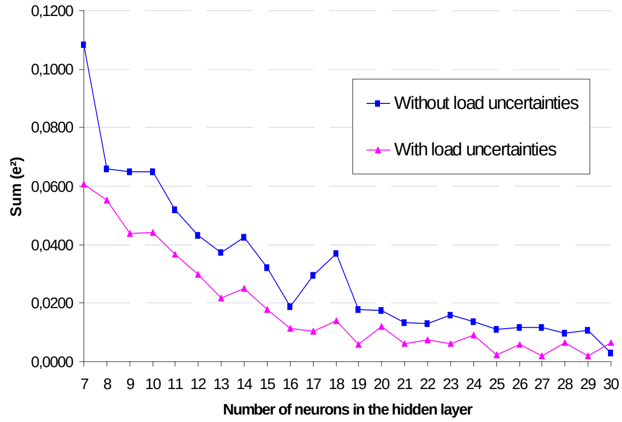

Figure 10 – Learning Mode Performance Functions for F_6.

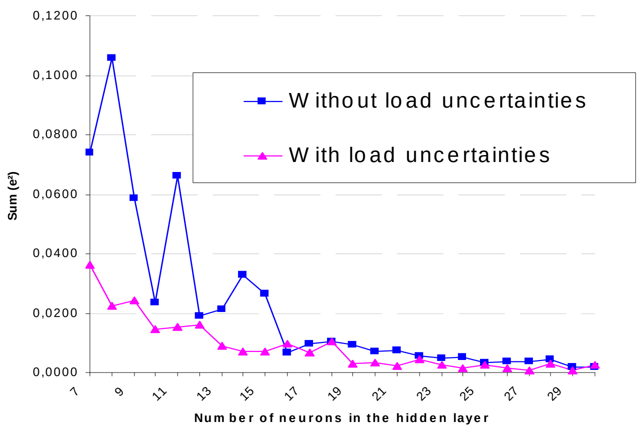

Figure 8 – Learning Mode Performance Functions for F_4.

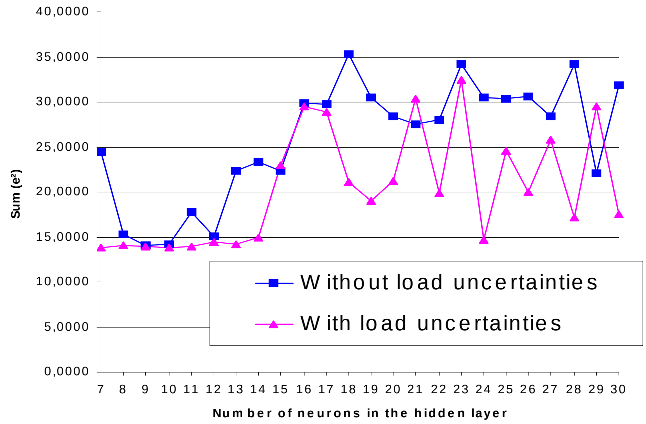

Figure 11 – Performance Functions for the second calibration.