ANGLES OF ATTACK AND SIDESLIP RECONSTRUCTION USING NEURAL NETWORKS

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ABSTRACT

This work is part of the research developed at the Department of Aerospace Engineering of the University of Pisa, concerning the definition of models and methods for the air data integration in the Flight Control System Fly-by-Wire of the aircraft Aermacchi M346.
The air data system, through dedicated computational procedures, determinates flight parameters (static pressure, Mach number, angles of attack and sideslip) from measurements of local pressure and local flow angles, provided by a proper set of probes, installed on the aircraft fuselage.
This work illustrates a procedure for the computation of the angles of attack and sideslip, based on Back Propagation neural networks. Such an approach is demonstrated to be an interesting alternative to the algorithms based on polynomial calibration functions. An optimization process on neural parameters (neurons number, iterations number, training algorithms, ...) has been carried out in order to define a neural architecture able to assure an adequate level of performance, according to the requirements of the modern Flight Control System. The used aerodynamic database has been carried out from the wind tunnel tests performed on a scaled model of the Alenia Aermacchi M346. In addition, a performance analysis has been developed both in full-operative condition and in presence of one or more probes in failure.

1. INTRODUCTION

The application of the artificial intelligence techniques to elaborate the air data parameters is described in this work. Previous works [1] have had the function of evaluating the feasibility of the neural approach to the static pressure and Mach number computation as an alternative to the classical approach [2].
The present work describes a study on elaboration algorithm constituted by several neural networks, able to substitute calibration polynomial functions in the angles of attack and sideslip reconstruction. The networks have been only used in the computational process of the aerodynamic angles while the algorithms able to manage the redundancies and identify the possible failures are the same used in [3].

Artificial Neural Networks (ANNs) are brain-style computational models, able to simulate the behaviour of a real system, composed of processing elements called nodes, with each node having several input branches but only one output branch as showed in FIG. 1. An ANN is usually composed of many nonlinear computational elements. They operate in parallel to simulate the function of a human brain. Hence, an ANN is characterized by the topology, activation function and learning rules. The topology is the architecture of how neurons are connected, the activation function is the characteristics of each neuron and the learning rule is the strategy for learning.

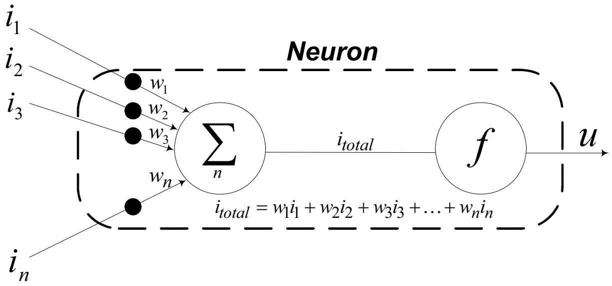

FIG. 1: Single processing element

In particular, each input connection to a node has a weight associated. The input values are multiplied by the associated weights and summed together with a node bias value.
An activation function then acts on the summed value producing the output value for the node.
An artificial network is constituted of several layers of nodes where the first layer typically has as many nodes as input variables.
Despite not necessary, the same transfer function is applied to the neurons that belong to the same layer. Various transfer functions are available, as showed in FIG. 2.
The FIG. 3 shows the organization of a neural network in two layers. This architecture is called Multi-Layer Perceptron (MLP) and it is the most used one, [4]. The number of hidden or output layers is application dependent.
The neuron's behaviour depends on its transfer function and on the balanced connections through which information are transferred. Neurons are very often fully interconnected with each other.

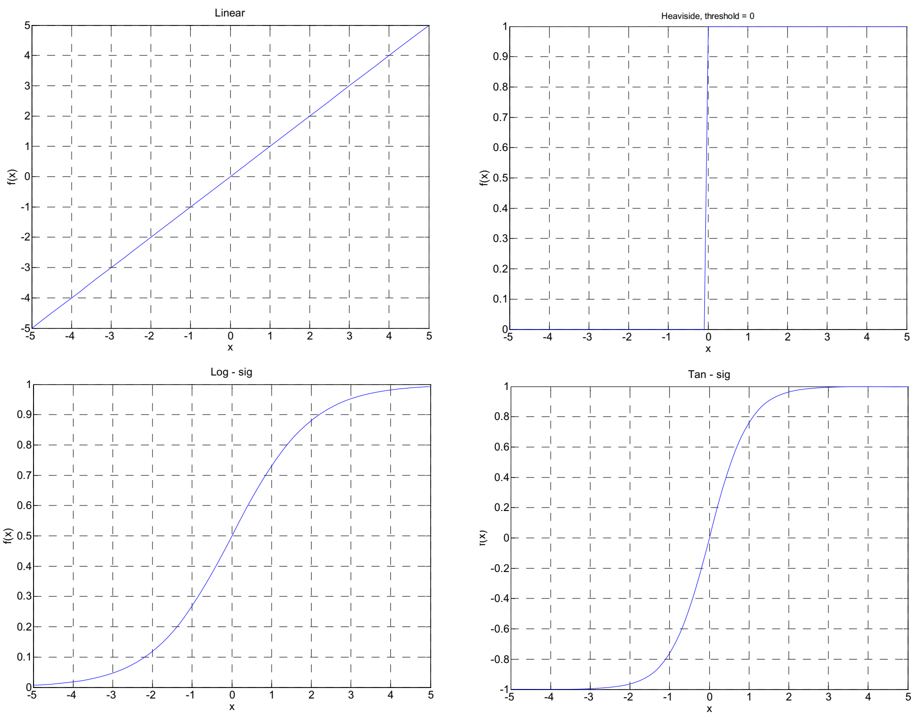

FIG. 2: Examples of transfer functions

In literature, it is possible to find methodologies called pruning or surgerying, [4] that can be used to cut some connections in order to improve performance, decreasing computational cost.

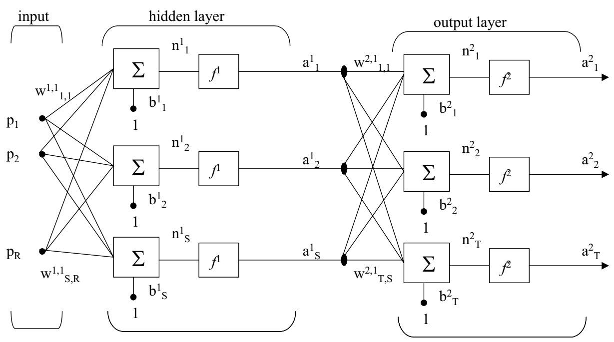

FIG. 3: Example of a Multi-Layer Perceptron, MLP

An ANN learns by adjusting the values of its weights through a training process. The training process consists of giving the neural network sample input-output data pairs and letting the neural network algorithm adjust the weights until it can produce the correct output for each input. This procedure is called supervised learning.
Back Propagation is one method of self-correction. During this process, input is applied to the first layer of a neural network and propagated through until an output is generated at the last layer of the neural network. The output obtained through forward propagation is then compared with the desired output to generate an error signal. The error is then distributed back to the nodes of the previous layer according to their contribution to the error. This process is repeated for all the layers, updating the weights. The neural network is iteratively trained with several input-output vector sets until it has all the training data encoded into it. It is important to note that the trained networks will perform only as well as the training data allows. For this reason, care should be taken in selecting the set of training vectors.
For an unsupervised learning rule, the training set consists of input training vectors only. The training process ends when comparable input vectors activate the same output (cluster).
It is possible to find several training algorithms characterized by different steps and research directions. In this paper the Levenberg-Marquardt supervised training algorithm, normally applied in the modern engineering, has been used.

2. ANGLES OF ATTACK AND SIDESLIP RECONSTRUCTION

The air data system studied in this paper is composed by four self-aligning air data probes named Integrated Multi Function Probe of Avionics Specialties, Inc. installed on the fuselage of the Alenia Aermacchi M346.
Each probe provides three outputs: the local flow angle λ_i measured by a rotary transducer (where subscript $i = 1,\ldots,4$ refers to the probe number); the frontal pressure $P_{front\ i}$ ("like total" pressure) provided by the frontal slot aligned with the local flow direction and the slot pressure $P_{slot\ i}$ ("like static" pressure). The latter is obtained as the

average of the pressures measured by the two slots at 90° from the local flow direction.

The networks relevant to the estimation of angle of attack and sideslip have two hidden layers of neurons and an output layer of a single neuron or of two neurons.
The neural networks have been trained on data set (*training set*) by means of the *Bayesian Regularization* and *Early Stopping* methods. The neural networks are excellent tools for interpolating a given set of data, if the training process uses subset points which properly represent the entire operating domain. Therefore, it is very important that training subset include an opportune number of points belonging to the border of the flight envelope.

The input signals are very important for the application of the neural networks to the estimation of the angles of attack and sideslip. Considering the mathematical model developed in [2], the following dependencies can be assumed:

(1) $$\lambda_{\_i} = f_i(\alpha, \beta, M_\infty, \underline{\Omega}, Config)$$

(2) $$P_{front\,\mathrm{i}} = P_{sa}\left[1 + \frac{\gamma}{2} M_\infty^2 \cdot Cp_{front\,\mathrm{i}}(\alpha, \beta, M_\infty, \underline{\Omega}, Config)\right]$$

(3) $$P_{slot\,\mathrm{i}} = P_{sa}\left[1 + \frac{\gamma}{2} M_\infty^2 \cdot Cp_{slot\,\mathrm{i}}(\alpha, \beta, M_\infty, \underline{\Omega}, Config)\right]$$

where $C_{pfront\ \mathrm{i}}$ e $C_{pslot\ \mathrm{i}}$ are the frontal and slot pressure coefficients of the i–th probe.
In the hypothesis the Mach number is known,(provided by an independent computation) and for assigned angular rate $\underline{\Omega}$ and aircraft configuration *Config*, by eq. (1) referred to angles measured by two generic probes (i-th and j-th probe) is possible to estimate the angles of attack and sideslip by means of the determination of the inverse function:

(4) $$\alpha = g_\alpha(\lambda_\mathrm{i}, \lambda_\mathrm{j}, M_\infty, \underline{\Omega}, Config)$$

(5) $$\beta = g_\beta(\lambda_\mathrm{i}, \lambda_\mathrm{j}, M_\infty, \underline{\Omega}, Config)$$

In this paper, we refer to a condition of rectilinear motion and fixed aircraft configuration named *Cruise* (with aerodynamic control surfaces frozen, landing gear retracted, absence of external stores and not taking into account the airflow through the engine).

For this reason we neglect the $\underline{\Omega}$ and *Config* parameters and the eq. (4) and (5) allow the calculation of one estimate of the angles of attack and sideslip, known the Mach number M_∞. This latter depends highly on the pressure ratios P_{front} / P_{slot} of the each probe. For this reason the Mach number information can be provide by the pressure ratios P_{front} / P_{slot} obtained by the probe measurements. In addition, it is worth noting that such pressure ratios are not much sensitive to the angles of attack and sideslip varying.

The six possible couples (λ_i, λ_j) allow six different couples (α_{ij}, β_{ij}) to be estimated, consequently it is possible to obtain six neural networks for α estimation and six for β estimation.

Three configurations of neural networks, with different input signals, have been considered. To identify the generic neural network, the wording "NN" is followed by the subscript word, related to the input signal, and apex word, related to the output signals. For example, subscript "$L1L2M_\infty$" points out that neural network inputs are λ_1, λ_2 and the Mach number M_∞, while apex "AoA,AoS" points out that neural network outputs are the angles of attack and sideslip.

The considered architecture are:

- Six neural networks $NN_{LiLjM_\infty}^{AoA}$ and six neural networks $NN_{LiLjM_\infty}^{AoS}$ at single output and six neural networks $NN_{LiLjM_\infty}^{AoA,AoS}$ at double output. Such networks have the angle measurements of two generic probes (λ_i, λ_J) and the asymptotic Mach number M_∞ (evaluated by an independent computation process) as input signals;
- Six neural networks $NN_{LiLjPiPj}^{AoA}$ and six neural networks $NN_{LiLjPiPj}^{AoS}$ at single output and six neural networks $NN_{LiLjPiPj}^{AoA,AoS}$ at double output. Such networks have the angle measurements of two generic probes (λ_i, λ_J) and the pressure ratios $P_{front\mathrm{i}}$ / $P_{slot\mathrm{i}}$ and $P_{front\mathrm{j}}$ / $P_{slot\mathrm{j}}$ concerning to the generic couple of probes (i, j);
- Six neural networks $NN_{LiLjPvot}^{AoA}$ and six neural networks $NN_{LiLjPvot}^{AoS}$ at single output and six neural networks $NN_{LiLjPvot}^{AoA,AoS}$ at double output. Such networks have the angle measurements of two generic probes (λ_i, λ_J) and the voted pressure ratio $(P_{front} / P_{slot})_{\mathrm{vot}}$ obtained from the four pressure ratios $P_{front\ \mathrm{i}}$ / $P_{slot\ \mathrm{i}}$.

The neural network predicted values have been processed by the voting algorithms described in [3] which provide a consolidated single value for α and β. The voted values are necessary to the other computational units and functions of the Flight Control System.

The networks relevant to the third typology have as input the pressure ratio $(P_{front} / P_{slot})_{\mathrm{vot}}$ which changes depending on the number of the pressure failures.

- **full-operative condition**: $(P_{front} / P_{slot})_{vot}$ is the average of the two middle values between the four ordered $(P_{front} / P_{slot})_i$ values;
- **one pressure failure**: $(P_{front} / P_{slot})_{vot}$ is the middle of the three remaining ordered values;

- **two pressure failures**: $(P_{front} / P_{slot})_{vot}$ is the average of the remaining estimates relevant to the probes not in failure.

For example, the voted pressure ratio is plotted in FIG. 4 as a function of both α and β for various Mach number values.

All the developed networks have three layers of neurons (FIG. 5), two hidden layer of 20 neurons each with a sigmoid activation function and an output layer (single neuron for the networks at single output and two neurons for the networks at double output).

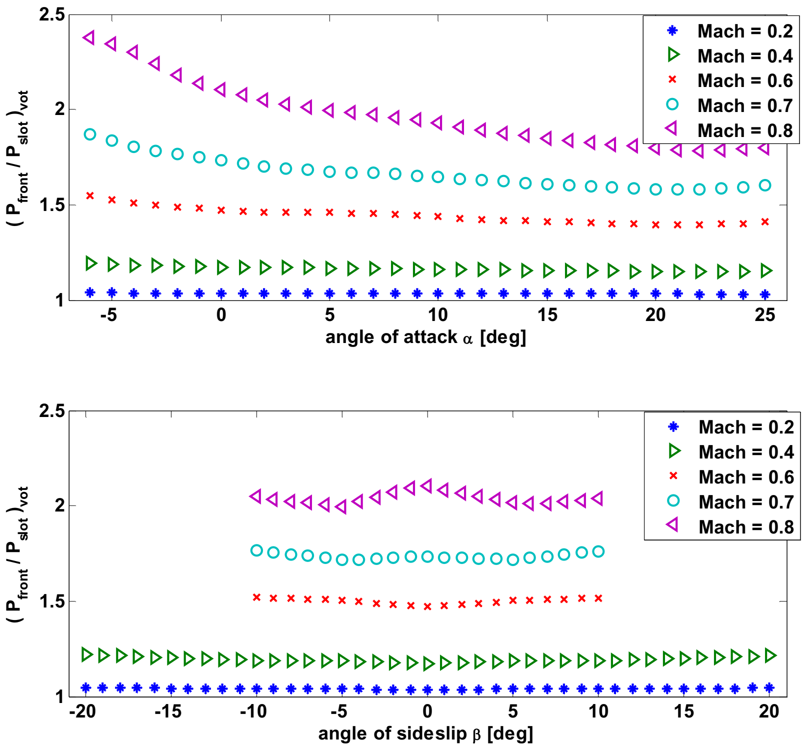

FIG. 4: Voted pressure ratio vs α, β and Mach

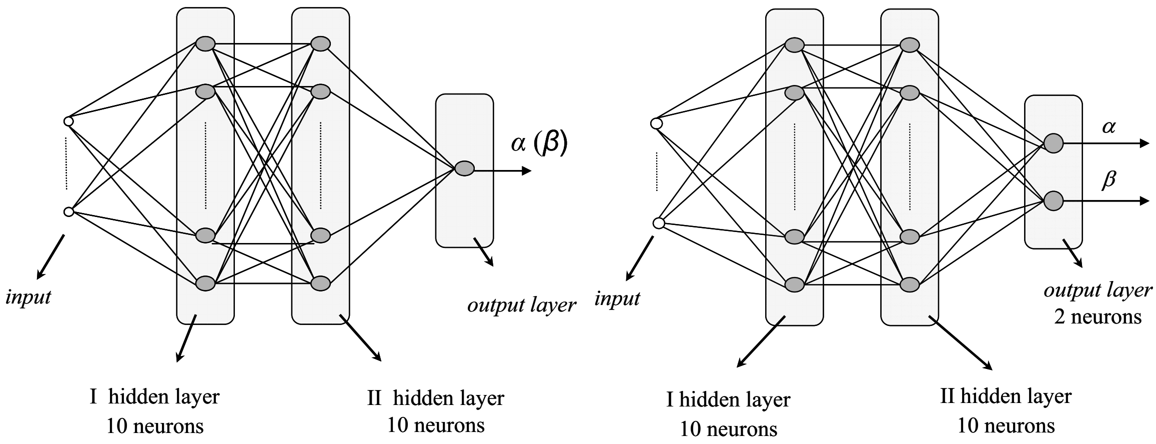

FIG. 5: Neural architectures with single and double output

3. NETWORK TRAINING PROCESS WITH WIND TUNNEL DATABASE

The neural networks illustrated in the previous section have been trained by using the wind tunnel database relevant to the new jet trainer Alenia Aermacchi M346. Such data points coincide with those used to tune the coefficients of the polynomial functions [2].

Training, validation and test data set have been determined by the random extraction of points from the data set.

The neural networks are excellent tools for the interpolation of a given set of data but not for its extrapolation. Therefore, it is necessary to use in the training process subset points which properly represent the entire operating domain.

The used technique [5] for searching of the training points consists in dividing all the data set into equal three-dimensional bins (α, β, M_∞). The random extraction from the bins of the 3400 points has given the best results. The original database must also be used to provide a complementary test set (and validation set) to measure the network ability in the generalization of different data from those of the training set. No border point is contained in the validation set even if it is constructed like the training one. The testing set includes all that points not belonged to the previous training and validation set. The 3400 random points, uniformly distributed into the domain of interest, have been divided in the following subset: 900 points for training set, 500 points for validation set and 2000 point for test set.
The examined data points refers to different asymptotic flow conditions characterized by the following Mach number, angle of attack and sideslip ranges: $0.2 < M_\infty < 0.8$, $-15 < \alpha < 30$ deg, and $-20 < \beta < 20$ deg.

FIG. 6, graphing the Mach number as a function of the angles of attack α and sideslip β, shows the training, validation and test points.

Both the Early Stopping and the Bayesian Regularization (training and validation into unique data set) algorithms have been used for the training process. Comparing the two algorithms, the Bayesian Regularization training process has been found to work better because it has guaranteed an overall lower level of error than the Early Stopping method.

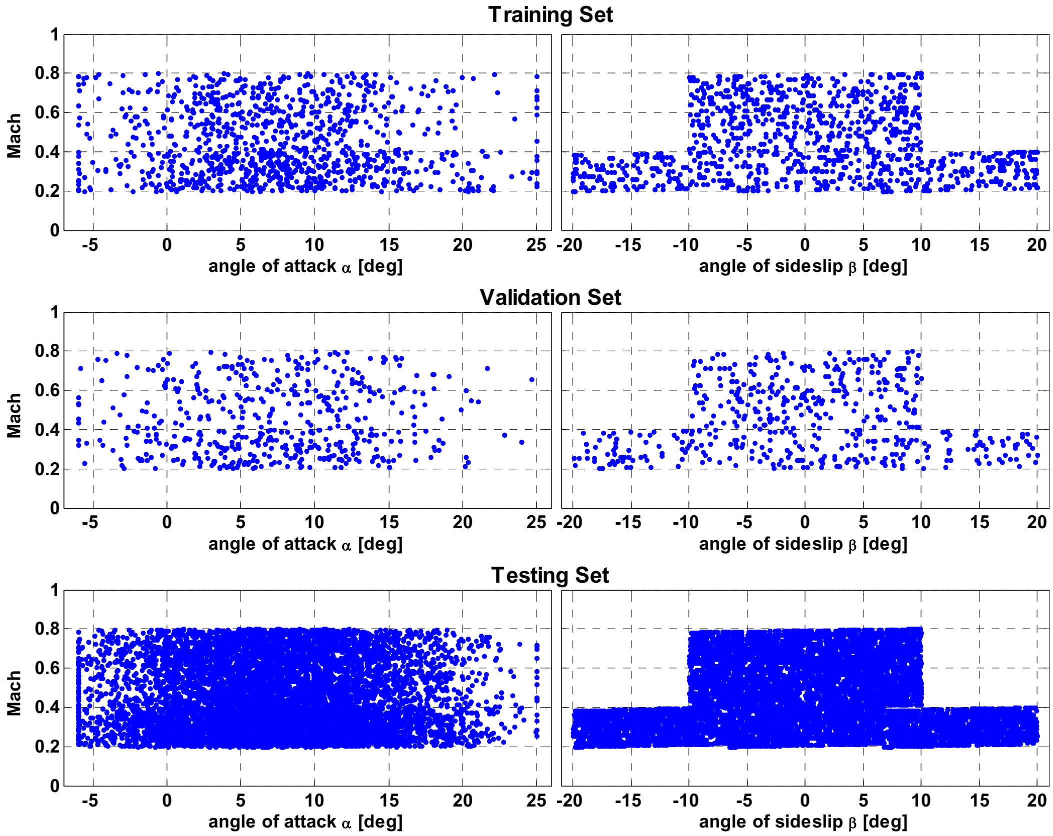

FIG. 6: Training, validation and testing data points

4. NETWORK'S BEHAVIOUR IN FAILURE CONDITION

Once the neural networks performance has been verified in full operative condition, a robustness analysis of networks performance was carried out when local angles or pressure failures occur.
Notice that, for all the considered neural networks, the effect of a local angle failure is to disable those networks which have it as input signal.

From the above, it is obvious that, if two angle measurements fail, only one couple of angles (λ_i, λ_J) is available. Consequently, one neural network can be used and only one couple of the angles of attack and sideslip can be predicted. However, in this case it is not possible to accept such solutions because they cannot be monitored.
The details of correlation between local angles failures and available neural networks are specified in TAB. 1.
Notice that all types of neural networks configurations are similarly affected by the local angles failures, while

the same cannot be said for the pressure failures. The neural networks ($NN^{AoA}_{LiLjPiPj}$, $NN^{AoS}_{LiLjPiPj}$, ecc.) which have as input the pressure ratio P_{front} / P_{slot} of the generic couple of probes are inhibited when a pressure failure occurs.
One pressure failure disables six neural networks with a single output (three for α and three for β) and three networks with double output. In the presence of double pressure failure, only two networks with single output (one for α and one for β) and only one network with double output is available.

Network configurations / Failures number	$NN^{AoA}_{LiLjM_\infty}$ $NN^{AoS}_{LiLjM_\infty}$	$NN^{AoA,AoS}_{LiLjM_\infty}$	$NN^{AoA}_{LiLjPiPj}$ $NN^{AoS}_{LiLjPiPj}$	$NN^{AoA,AoS}_{LiLjPiPj}$	$NN^{AoA}_{LiLjPvot}$ $NN^{AoS}_{LiLjPvot}$	$NN^{AoA,AoS}_{LiLjPvot}$
No failure	12 (6+6)	6	12 (6+6)	6	12 (6+6)	6
One angle failure	6 (3+3)	3	6 (3+3)	3	6 (3+3)	3
Two angle failures	2 (1+1)	1	2 (1+1)	1	2 (1+1)	1

TAB. 1: Number of available neural networks correlated to local angles in failure

Concerning the neural network using as input the voted pressure ratio (P_{front} / $P_{slot})_{vot}$, note that no neural network is disabled when a failure pressure occurs. However the pressure failure influences the neural network estimate values of the angles of attack and sideslip. In fact as noted earlier, (P_{front} / $P_{slot})_{vot}$ value changes depending on the number of the pressure ratios that are available.
The neural networks have been trained in full operative condition (all four pressure available), so when pressure failures occur, (P_{front} / $P_{slot})_{vot}$ value changes and degraded accuracy outputs have to be expected.
A lower accuracy also characterizes the neural networks $NN^{AoA}_{LiLjM_\infty}$, $NN^{AoS}_{LiLjM_\infty}$ and $NN^{AoA,AoS}_{LiLjM_\infty}$ when the pressure measurement failures occur. In fact, such event causes an higher error on the Mach estimate provided by an independent computation algorithm (i.e. polynomial functions or neural networks) depending from pressure measurements (see [1], [2])

5. RESULTS

All the neural networks, trained on the wind tunnel database, with the methodology described in the previous paragraphs, have given good results. Notice that the errors of the neural networks relevant to the estimation of the angle of attack and sideslip are on the order of 10^{-2} deg for the average absolute errors (standard deviation has the same order) and are on the order of 10^{-1} deg for the maximum absolute error. These performances are achieved on both full operative system condition and when one or more failures occur. For these reasons, it can be observed that the choice of the input correlated to the pressure measurements (asymptotic Mach number, pressure ratios P_{front} / P_{slot} of generic couples of probes or voted pressure ratio) does not significantly affect the prediction accuracy on estimation of angle of attack and sideslip.
The neural networks which have as input the voted pressure ratio (P_{front} / $P_{slot})_{vot}$ are to be preferred because they are not affected by other source errors coming from different estimation algorithms (estimation of Mach number) and no network is disabled in failure condition.
By comparing the different neural networks developed, the analysis of accuracy points out that the architecture with a double output has the advantage that allows analogous performance respect to the single output architecture, at lower number of coefficients to be stored.
FIG. 7 shows a comparison between the angles of attack and sideslip provided by neural networks $NN^{AoA,AoS}_{LiLjPvot}$ and the nominal values referred to a full operative condition, to one and two pressure failures. Notice that the estimates refer to voted values provided by voting algorithms illustrated in [3], which provide a consolidated value for angle of attack and angle of sideslip on the basis of the six neural networks. Every point in the figure represents the average of the estimates obtained by the neural networks for the following Mach number values: 0.2, 0.3, 0.4, 0.5 ,0.7 and 0.8.

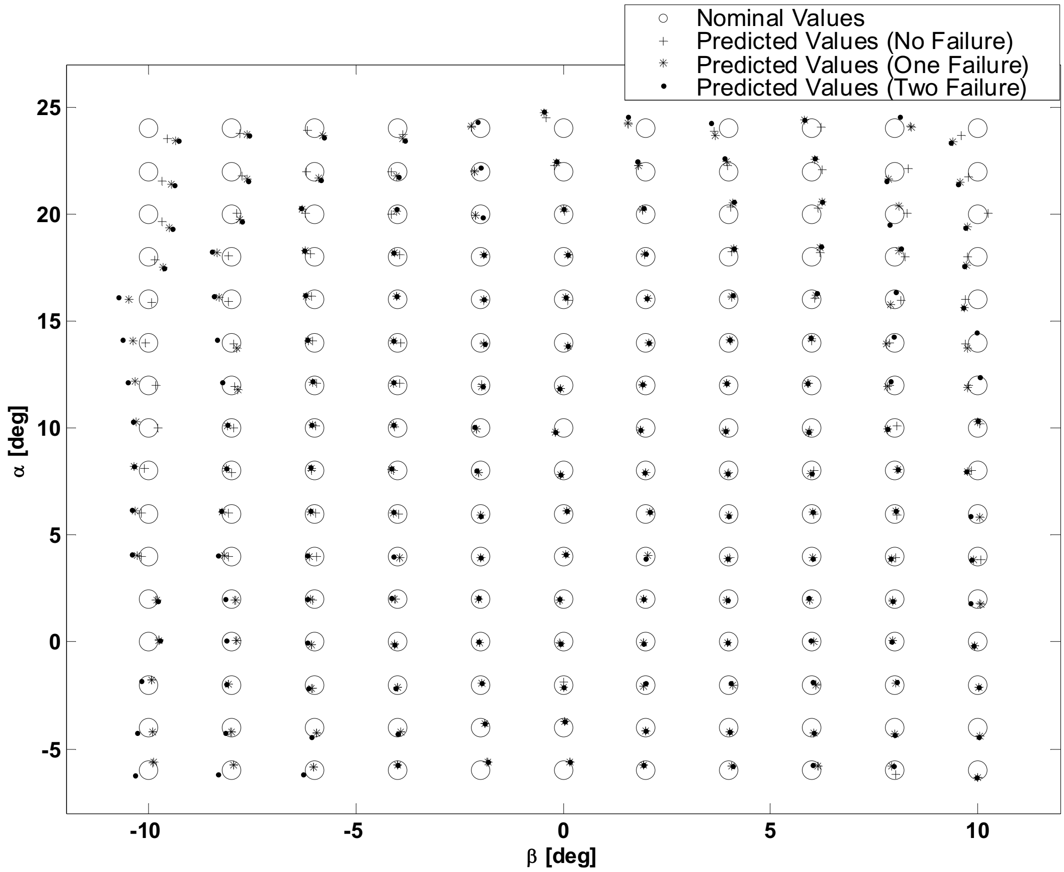

FIG. 7: Predicted and nominal values of angles of attack and sideslip in several operative conditions

CONCLUSION

The feasibility of the neural approach has been evaluated for the computation of the angles of attack and sideslip, as alternative to the classic algorithms. Such an approach is demonstrated to be an interesting alternative to the algorithms based on polynomial calibration functions [1] for the computation of the Mach number and static pressure.

Several neural architectures have been considered, characterized by a different input and output number. All the neural networks have been trained on the wind tunnel database performed on the model of the Alenia Aermacchi M346. Such database has also been used to tune the polynomial calibration functions [2]. Each architecture has showed a good performance both in full-operative condition and in presence of one or more probes in failure.

A peculiar feature of the neural networks to be considered is that they show dramatic advantages in terms of time to be spent to tune the system in the presence of the new data (coming either from flight tests or from modifications of the aircraft configuration).

Concerning the manoeuvres with high angles of attack, the asymptotic parameters are connected to the local measurements through complex functions. The use of a classic approach can result complex because it would need a high number of polynomial functions which can to be difficult to manage. In the case of neural networks, the only increase of neurons number is sufficient as often as not, without to reconfigure the neural architecture.

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