New Approach for the Identification and Validation of a Nonlinear F/A-18 Model by Use of Neural Networks

Nicolas Boëly and Ruxandra Mihaela Botez

***Abstract*—This paper presents a new approach for identifying and validating the F/A-18 aeroservoelastic model, based on flight flutter tests. The neural network (NN), trained with five different flight flutter cases, is validated using 11 other flight flutter test (FFT) data. A total of 16 FFT cases were obtained for all three flight regimes (subsonic, transonic, and supersonic) at Mach numbers ranging between 0.85 and 1.30 and at altitudes of between 5000 and 25 000 ft. The results obtained highlight the efficiency of the multilayer perceptron NN in model identification. Optimization of the NN requires mixing of two proprieties: the hidden layer size reduction and four-layered NN performances. This paper shows that a four-layer NN with only 16 neurons is enough to create an accurate model. The fit coefficients were higher than 92% for both the identification and the validation test data, thus demonstrating accuracy of the NN.**

***Index Terms*—Aeroservoelasticity, aircraft validation and identification, flight flutter tests, neural network.**

I. Introduction

OVER the last two decades, a great deal of attention has been directed at multilayer neural network (NN) theories through studies and developments in a wide range of fields, such as pattern classification, model identification, and control. It has been demonstrated that NNs in general, and multilayer perceptron NNs in particular, could serve as universal approximators for unknown systems or unknown mathematical functions. In [1] it was proved that multilayer feed forward NNs, composed of a finite number of neurons and arbitrary activation functions, were universal approximators. A mathematical proof of this type of universal identification has been demonstrated [2]–[4].

As far as hidden neurons are concerned, an *over-sized* network could *over-fit* the noise included in test data and *over-learn* it for a special data set, in which case the adaptation to unknown test data should be an issue due to the *over-training*. Conversely, a hidden layer that is too small could significantly reduce the results accuracy. Reference [5] suggested the use of an NN genetic algorithm in order to optimize the data, but this method was, however, computationally time consuming.

Destructive and pruning methods are also available for finding the NN size for model identification: the destructive methods consist in a step-by-step deletion of useless or redundant neurons in an oversized network [6], while the pruning methods provide a real-time improvement of the NN performance by increasing the hidden layer size [7]. A logarithmic function was used in [8] to empirically demonstrate the direct relationship between the number of identification iterations and the hidden layer size. They used the entropy theory to evaluate the effectiveness of the trained NNs.

NN methodologies could thus be used to identify any aeroelastic model, as is the case in this paper. The other crucial parameter in the NN architecture is the choice of the activation function. The application of NN to a real-world system remains a challenge in system identification. Backpropagation NNs are the most commonly used NNs. Indeed, two other studies were performed in our laboratory on the F/A-18 model identification; the first study was based on the combination of NN and fuzzy logic, which was presented in detail in [9], while the second study was based on fuzzy logic methodologies, as was shown in [10].

Although NNs have been studied for many years, there is still no efficient method for calculating optimal NN parameters, such as the layer size, the number of neurons, and the number of iterations required to train the NN. Besides, the identification data must be chosen carefully, otherwise, *under-learning* could occur, leaving the NN unable to fit any data. The other crucial parameter in the NN architecture is the choice of the activation function [see Fig. 6 and (2)]. The way in which these parameters are chosen is explained in Section III-A.

NNs are not often used to identify aircraft's aeroelastic behavior, nevertheless, they are used to predict the flight flutter speed. A description and the results are available in [11].

In this paper, the aeroservoelastic F/A-18 model is identified and validated using NN algorithms, and NN parameters are properly sized. To obtain the required adaptation and generalization capabilities for different flight flutter cases, the NN must be trained. Section II states the problem, while Section III establishes the optimal parameters required to train

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N. Boëly was with the Laboratory of Applied Research in Active Controls, Avionics and Aeroservoelasticity, Ècole de Technologie Supérieure, University of Quebec, Montreal, QC H3C-1K3, Canada. He is now with Bombardier Aerospace, Montreal, QC H4S-1Y9, Canada (e-mail: nicolas.boely.1@etsmtl.ca).

R. M. Botez is with the Department of Automated Production Engineering, Laboratory of Applied Research in Active Controls, Avionics and Aeroservoelasticity, Ècole de Technologie Supérieure, University of Quebec, Montreal, QC H3C-1K3, Canada (e-mail: ruxandra@gpa.etsmtl.ca).

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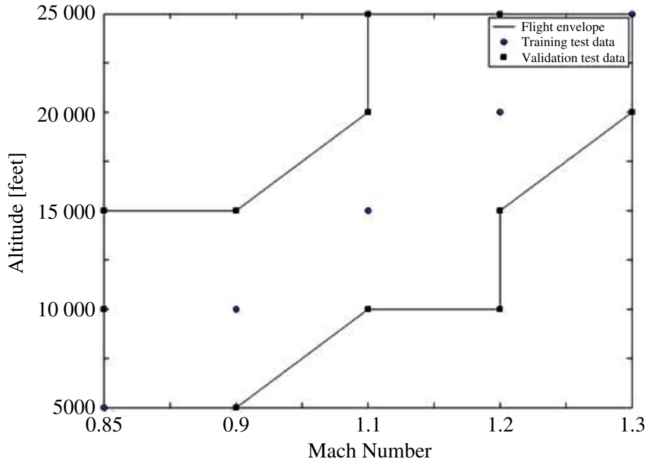

Fig. 1. Flight cases used for identification vs. flight cases used for validation.

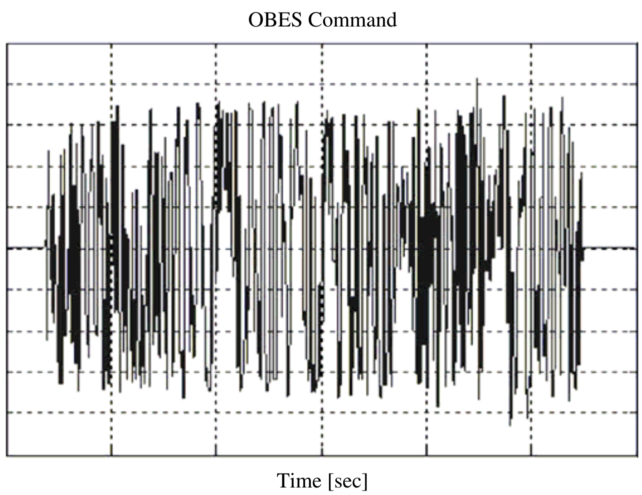

Fig. 2. OBES control inputs vs. time.

the NN model identification. Results obtained with the new NN method are shown in Sections IV and V, and conclusions are presented in Section VI. In this paper, the F/A-18 aeroservoelastic model identification is validated using different flight flutter test (FFT) data from those used for the model identification using the new NN methodologies.

II. Problem Statement

Aeroservoelastic interaction studies include the investigation of surface deformations of aircraft structures and their interactions with the aircraft controls. In this paper, a nonlinear F/A-18 aircraft model is built by linking the control surface deflections to the aircraft's structural deflections. Sixteen different FFT data expressed in terms of different Mach numbers and altitudes were collected and provided to us by NASA's Dryden Flight Research Center (DFRC) laboratories. We divided these 16 FFT cases into two types of FFT data: five were used for the NN model identification and 11 for the NN model validation, as shown in Fig. 1.

In order to obtain the recorded FFT data shown in Fig. 1, the flight control computer was modified by adding a research flight control system to generate the Schroeder frequency

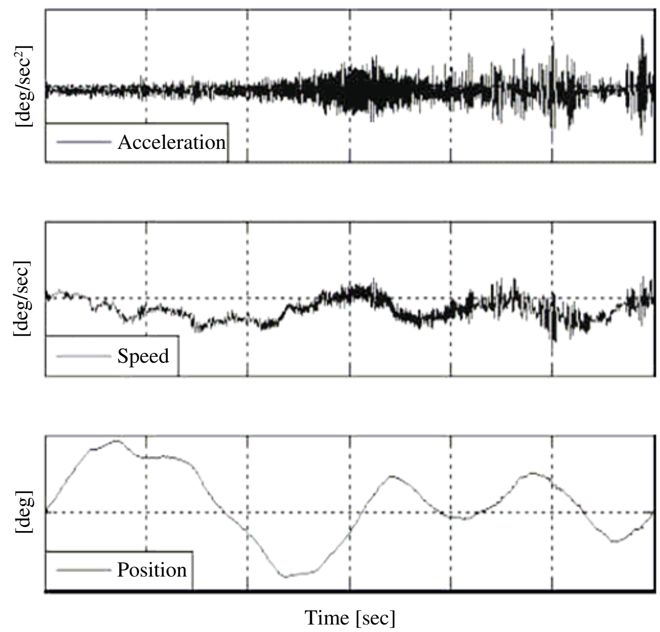

Fig. 3. Left wing accelerations, speeds, and deflection positions-variations with time.

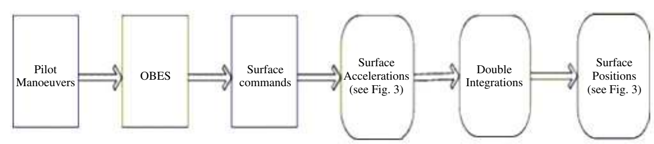

Fig. 4. FFT data processing scheme.

sweep control inputs. This processor was activated by the pilot with a cockpit switch. The software used to control the actuators was called the On-Board Excitation System (OBES). The input activated by the OBES was a Schroeder frequency sweep equally spaced in the frequency domain. An example of the OBES controls is shown in Fig. 2.

The OBES Schroeder excitation signal is defined as

$$\mathrm{OBES}(t) = \sum_{k=1}^{S} \mathrm{A_k} \sin\left(2\pi f_k t + \varphi_k\right) \tag{1}$$

where f_k is the kth measurement frequency, φ_k is the kth phase and A_k is the kth amplitude of the OBES Schroeder signal. Details of the Schroeder signals theory are given in [12]. The OBES Schroeder signals were sent to the aircraft actuators to generate the F/A-18 control surface oscillations. Records of structural surface accelerations were obtained at 30-s time intervals, and we integrated the accelerations twice to obtain the surface deflections [13]. These integrations remove noise disturbances due to accelerations, as shown at the bottom of Fig. 3, where variations in structural deflections with time are presented for the left wing.

In Fig. 4, the fast Fourier transform data-processing scheme explains how the surface positions were generated and therefore obtained from pilot manoeuvres.

The six inputs considered in Fig. 5 are the left and right aileron positions AIL_L and AIL_R; the left and right stabilizer positions STB_L and STB_R; and the left and right vertical tail

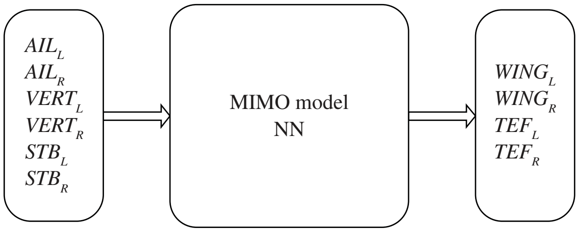

Fig. 5. Global representations of FFT input and output data.

positions $VERT_L$ and $VERT_R$. The four outputs are the left and right wing positions $WING_L$ and $WING_R$; and the left and right trailing edge flap positions TEF_L and TEF_R.

The multiple input–multiple output (MIMO) model linking the six inputs to the four outputs is clearly shown in Fig. 5. A specific NN architecture was chosen for the MIMO model, which was *trained* using only five flight flutter cases (see Fig. 1). The NN model was then validated by using the other 11 flight cases in order to validate the generalization ability of the model identification. This paper provides a new way of aircraft identification and validation using new NN methodologies, thus providing a better understanding of aircraft flutter behavior in three primary flight regimes (subsonic, transonic, and supersonic).

In this paper, the scales of the axes are not represented because of the confidentiality of data that were provided by the NASA DFRC.

III. NN Architecture

A. Methodology

In order to define the NN architecture, we must choose the values of its main five parameters, namely the input layer size, the hidden layer size, the output layer size, the number of neurons of each layer, and a proper identification dataset.

One neuron, composed of weights, bias, and an activation function, is defined in Fig. 6, where $d_j^{k-1}(j = 1, \ldots, N), d_i^k, f^k, w_{ij}^k$, and b_i^k are the input data, the output data, the activation function, the weights, and the biases of its kth layer. Such a neuron is expressed as

$$d_i^k = f^k\left[\sum_{j=1}^{N}\left(w_{ij}^k d_j^{k-1}\right) + b_i^k\right]. \quad (2)$$

There is no rule for the choice of the layer size. In order to simplify the NN identification model, is assumed that the input layer size would equal to its first hidden layer size. An increase in the number of neurons on the input layer would increase the number of useless or redundant neural weights for identification. Conversely, having a small number (one or two) of neurons on the input layer would decrease the generalization capacity of the model due to a lack of information. As far as the output layer is concerned, the choice is easier thanks to the fact that the output layer size must be the same as the output data size, which is 4 (see Fig. 5).

To finalize the general architecture, there is always the need to choose the hidden layer size. In [14], it was highlighted that an NN with no hidden layer size can only fit a linear function or a decision. One hidden-layer NN could approximate any function representing a continuous mapping on finite mathematical spaces. If one more hidden layer is added, the network could approximate any mapping with any accuracy. A four-layered NN was written in [15] that had higher generalization capacity than a three-layered one. We do not know what type of mapping could represent our system, and therefore two hidden layers are chosen to represent our NN.

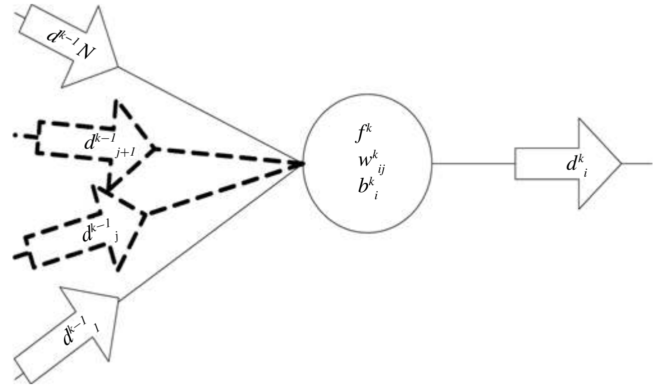

Fig. 6. kth neuron layer perceptron.

Rule-of-thumb methods have been explored in NN sciences to calculate the number of neurons. This number could be calculated either by taking the average between the input layer size and the output layer size or taking two-thirds of the input layer size plus the output layer size [14]. In [6], it was shown that, to avoid redundant neurons, an optimized layer should have between three and five neurons. In Section IV, the influence of the number of neurons and the generalization error on the identification model are analyzed.

The capabilities of three-layered and four-layered NNs were studied in [15]. They showed mathematically that a four-layered NN which has to give N outputs must have $(N/2+3)$ hidden neurons for any hidden layer. From this demonstration, we chose to use a four-layered NN. As far as its layer sizes are concerned, the input layer size and the output layer size have to be equal, respectively, to the number of inputs and the number of outputs. Thus, the NN has six inputs neurons whereas it has only four outputs neurons. Using the rule of Tamura and Tateishi, as we have four outputs signals, the number of hidden neurons must be equal to $(4/2+3)$, that is 5.

To put it in a nutshell, the NN of this FFT identification is composed of four layers. The first layer, which is called the input layer, has six neurons. The two hidden layer have both five neurons as shown in [15]. Finally, the output layer has four neurons.

This NN maps the FFT signals data for the entire flight envelope. The NN is trained with exclusively the five training test data. Its generalization capacity will be tested with all the flight validation test data signals.

B. NN Back-Propagation Algorithm Description

The back-propagation learning laws from the Levenberg–Marquardt algorithm, which is described in [16], are used in identification simulation.

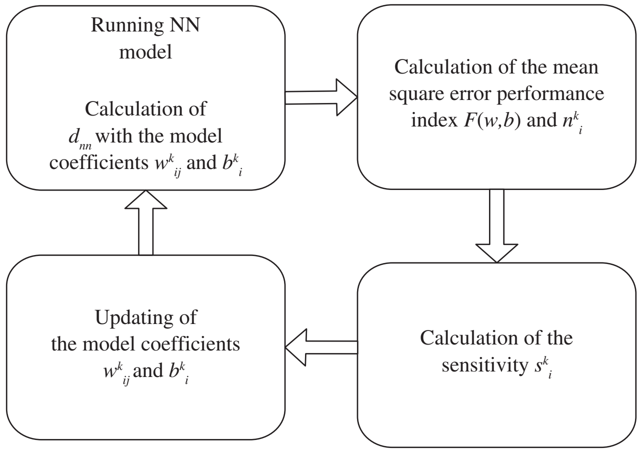

Fig. 7. Optimized updating of the weights and the biases during identification.

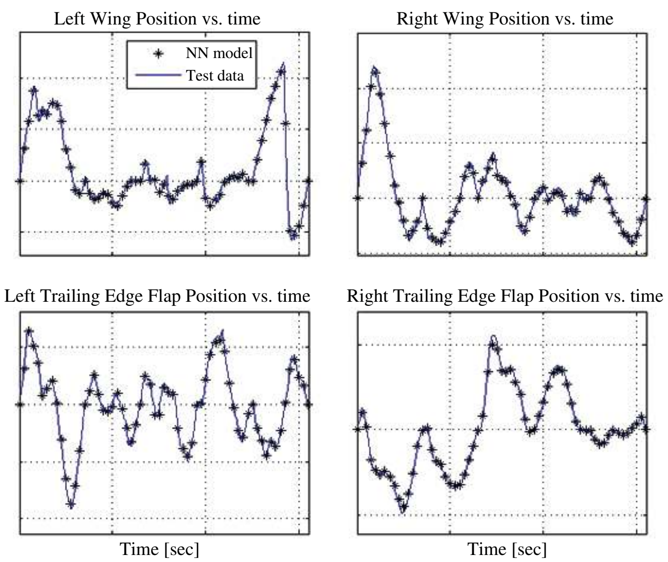

Fig. 8. MIMO model identification results for $M = 1.30$ and altitude $H = 25\,000$ ft.

The multilayer network back-propagation algorithm is a *gradient descent optimization* procedure, in which a mean square error performance index is minimized by adjusting the network parameters (weights w and biases b), as shown in [17]–[19].

We can say that the first step consists in the forward propagation of the input through the network, followed by the second step, which involves the calculation of the mean square error performance index of the NN model, the third, which is the backward propagation of the sensitivities through the network, and finally, the fourth step, which consists of an update of the biases and weights, see Fig. 7.

There are two cases to be considered: 1) if the entire squared error decreases after a weight and bias update, both updates are accepted and the learning rate is multiplied by a factor higher than 1, and 2) if the entire squared error increases by less than the defined percentage, then the weight and bias update are accepted, but the learning rate is unchanged.

One of back-propagation algorithm problems we must face is the achievement of a global or a local minimum. In both cases, the algorithm guarantees its convergence to a solution that minimizes the mean squared error, as long as the learning rate is not too high.

TABLE I

Fit Coefficients (%) for Five Identification FFT Data Model

Mach number	Altitude 10^3 ft	$WING_L$	$WING_R$	TEF_L	TEF_R
0.85	5	98.02	99.44	99.64	99.03
0.9	10	97.61	98.95	99.22	98.18
1.1	15	96.79	98.26	99.64	98.07
1.2	20	98.78	96.85	98.28	97.46
1.3	25	98.72	95.55	94.16	94.89

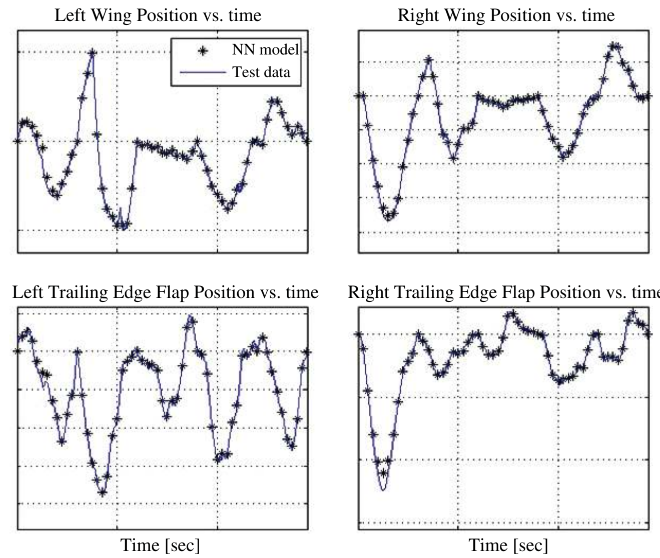

Fig. 9. MIMO aeroservoelastic model validation for $M = 1.10$ and $H = 25\,000$ ft.

As previously indicated, the weights and biases are chosen arbitrarily at the first iteration. To avoid a local minimum, several initial guesses are made in order to ensure convergence to the global minimum.

One criterion is applied to estimate the degree of the NN model identification and to determine whether it would fit the FFT data. The fit coefficient is expressed through (3)

$$FIT = 100\left[1 - \sqrt{\frac{\sum (t - d_m)^2}{\sum [t - mean(t)]^2}}\right]. \quad (3)$$

Equation (3) shows the definition of this criterion as the L_2-norm of the error between the FFT data and the NN model over the L_2-norm of the error between the FFT data and its mean value.

The mean values of the four output fit coefficients are compared to find out which NN case fits the best for our system (see Table I). Results are further analyzed on the basis of this criterion, using identification, validation, and robustness tests.

IV. Results

The NN model obtains fit coefficients between 94.16% and 99.64% for the five identification cases (Table I).

The worst NN model identification case is the one corresponding to the last row shown in Table I, and corresponding results are presented visually in Fig. 8.

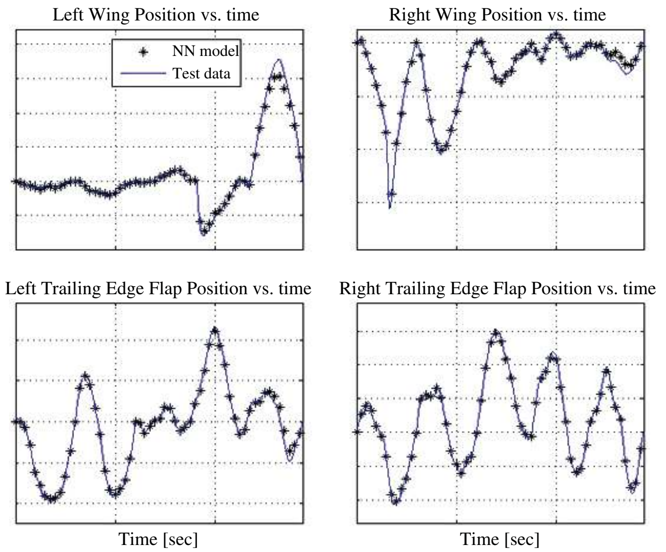

Fig. 10. MIMO aeroservoelastic model validation for $M = 1.20$ and $H = 10\,000$ ft.

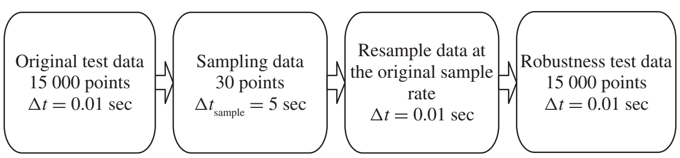

Fig. 11. Creation of robustness test data.

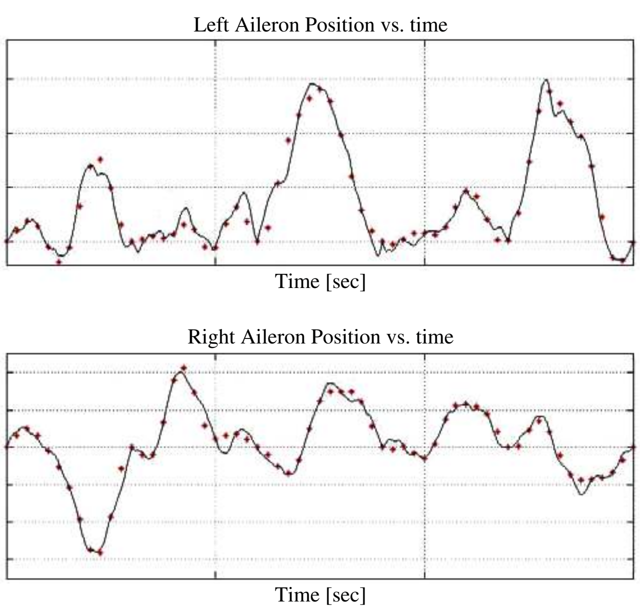

Fig. 12. Left and right aileron positions original signals, left and right aileron positions perturbed signals: variations with time.

V. Validation of the NN Identified Model

A. Generalized Capacity

Table II and Figs. 9 and 10 show the results obtained for the NN model identification and validation. In order to analyze the trained NN generalization abilities, the 11 other FFT tests (see Fig. 1) were considered for the NN model validation, while 5 FFT tests were considered for its identification. The fit coefficient values are shown in Table II.

TABLE II
Fit Coefficients for NN Model Validation by Use of 11 FFT Data

Mach number	Altitude 10^3 ft	$WING_L$	$WING_R$	TEF_L	TEF_R
0.85	10	97.93	98.46	98.31	97.32
0.85	15	98.45	98.25	98.28	97.13
0.9	5	93.26	95.47	96.95	96.88
0.9	15	94.75	98.52	98.68	97.35
1.1	10	98.24	98.85	99.19	97.58
1.1	20	97.66	98.81	96.97	96.65
1.1	25	93.30	96.54	95.11	91.00
1.2	10	89.29	92.04	92.16	96.70
1.2	15	98.54	98.08	98.28	97.90
1.2	25	97.22	98.48	97.84	97.11
1.3	20	92.62	93.04	95.31	98.12

TABLE III
Fit Coefficients for Robustness Test for All Flight Conditions

Mach number	Altitude 10^3 ft	$WING_L$	$WING_R$	TEF_L	TEF_R
0.85	5	77.84	80.79	83.80	86.90
0.85	10	89.99	94.40	79.51	87.33
0.85	15	83.68	81.24	87.85	85.48
0.9	5	87.93	92.07	91.58	87.12
0.9	10	89.32	90.72	87.10	79.54
0.9	15	83.90	92.78	86.01	88.30
1.1	10	83.13	78.76	89.60	81.03
1.1	15	79.25	90.37	89.49	90.26
1.1	20	87.11	90.34	83.65	86.89
1.1	25	83.40	89.41	79.17	85.71
1.2	10	86.37	76.68	88.19	86.95
1.2	15	84.89	91.23	88.76	78.95
1.2	20	84.79	92.56	89.32	88.65
1.2	25	90.46	91.23	87.78	90.18
1.3	20	76.98	84.63	93.36	83.37
1.3	25	76.78	83.76	81.39	88.38

These results demonstrate the accuracy of the NN identification flutter model with unknown flight test cases used for its validation. Even if the flight envelope is spread from $H = 5000$ ft to $H = 25\,000$ ft and from $M = 0.85$ to $M = 1.3$, we assume that this identification and validation dataset is a judicious choice representing an aircraft's aeroelastic behavior. The results obtained for the worst cases are shown in Figs. 9 and 10.

These results show the generalization ability of the NN model to fit FFT data that has never been trained. The fit coefficients for all validation FFT cases are higher than 90%.

B. Robustness Tests

The robustness of our estimated model was evaluated by considering the model's output resulting from a simulation using slightly perturbed input signals [13]. Actually, the perturbed input signals correspond to the original input signals that are sampled and re-sampled to obtain the original input signal sample time (Fig. 11).

The purpose of this test was to evaluate the effect on the model's output for negligible input signal perturbations.

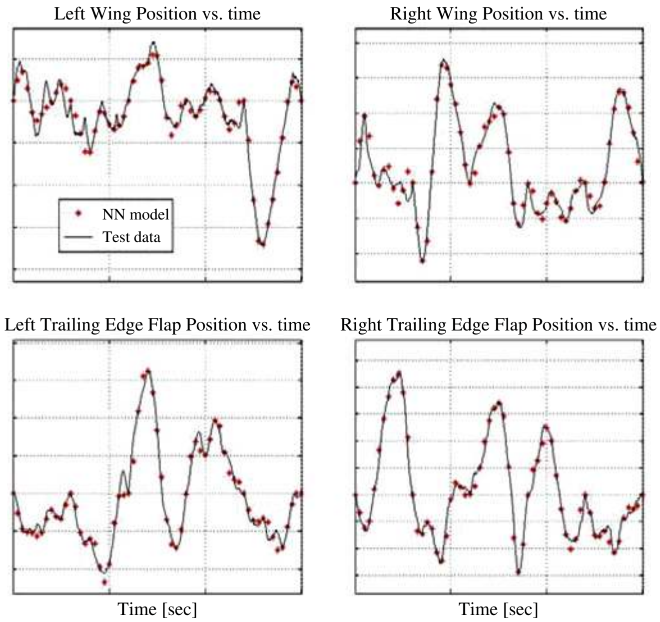

Fig. 13. Robustness test results for $M = 0.85$ and $H = 5000$ ft.

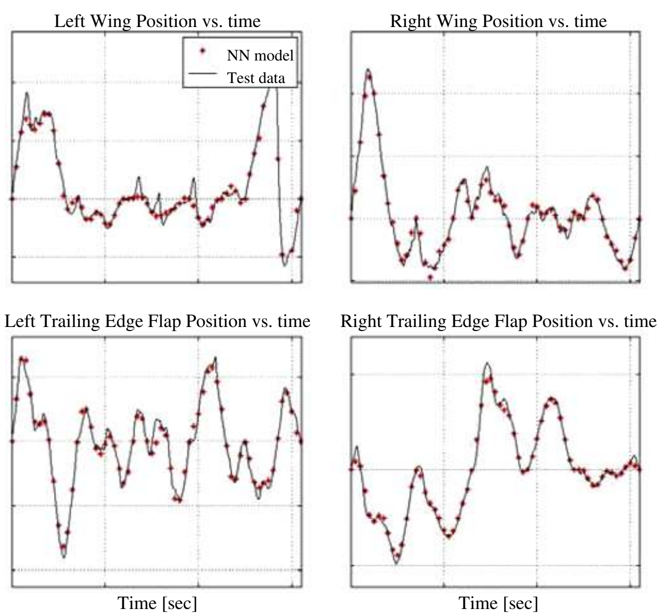

Fig. 14. Robustness test results for $M = 1.3$ and $H = 25\,000$ ft.

The model is considered robust if it is not sensitive to very small perturbations of its inputs.

The perturbed input signal was generated by performing the following operations: 1) re-sampling of the signal by keeping only one out of 500 points, and 2) reconstruction of the signal from these points by interpolations in order to obtain the initial sampling rate. This procedure is illustrated in Fig. 11, where Δt_{sample} is the sampling rate over the concatenated time interval of 150 s, which is equivalent to adding a large number of small perturbations to the input signals in order to measure the model sensitivity to these perturbations. If the NN model is robust, it must react very well to small perturbations of the input signals, which means that we have neither divergence nor oscillations on the output signals.

Next, Fig. 12 highlights the difference between the original left and right aileron position signals and the perturbed left and right aileron position signals.

Table III shows the fit coefficient values obtained for the NN model using the robustness test procedure. The values of these fit coefficients demonstrate the robustness of the NN model.

These results show the NN identification model accuracy. Even though the flight envelope covers a broad range going from $H = 5000$ to $H = 25\,000$ ft and from $M = 0.85$ to $M = 1.3$, the fit coefficients of the two worst robustness tests are higher than 76%. Figs. 13 and 14 show the robustness test results for the two worse cases.

VI. Conclusion

Sixteen FFTs for different combinations of Mach numbers and altitudes were used for NN model identification and validation in this paper. The NN algorithm was used for the model identification from FFTs. Two types of tests, namely *validation* and *robustness* tests, were used to evaluate the fit coefficients needed to quantify the aircraft model's performance.

The fit coefficients calculated through validation tests were found to be higher than 92.04%, while those obtained through robustness tests had the worst values (76.68%). Therefore, the estimated model fit the FFTs data very well. The lowest fit coefficient was obtained for the right wing position for the flight condition expressed by $M = 1.20$ and $H = 10\,000$ ft, while the highest was obtained for the right wing position for the flight condition expressed by $M = 0.85$ and $H = 10\,000$ ft. The trained NN model was validated using 11 other FFT data.

The NN identification method has the advantage of having a short computation time and estimates an excellent model from the flight test inputs and outputs without *a priori* knowledge about the aircraft model dynamics. The estimated model was found to be robust following an evaluation using the re-sampling technique. From the results obtained, it can be concluded that our NN method is extremely efficient for aircraft model identification based on known FFTs.

These results are better than those obtained for the previous identified state-space model, using the subspace method by Sandrine De Jesus Mota *et al.* [13]. The drawback of our NN method is its stability study, which would be more difficult to analyze using NN data than by using the state-space model. However, this new NN aircraft identification model has proven its ability to generate proper flight flutter deformations at a new flight envelope point. Thus, an MIMO nonlinear NN model could very well estimate structural surface deflections for 16 flight conditions.

This methodology allows us to compute nearly online an NN identification mapping of the aircraft's aeroelastic behavior. This was successfully obtained with FFT data signals provided by the NASA DFRC, with F/A-18 active aeroelastic wing A/C. This NN mapping would be used for the establishment of a flight flutter suppression controller in order to avoid flutter effects on structural and control deflections.

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Nicolas Boëly was born in Limoges, France, in 1984. He received the B.Sc. degree in aeronautics from Ecole Supérieure des Techniques Aéronautiques et de Construction Automobile, Paris, France, and the M.Sc. degree in aeronautics from the École de Technologie Supérieure, University of Quebec, Montreal, QC, Canada, in 2010.

He was working at the Laboratory of Applied Research in Active Controls, Avionics and Aeroservoelasticity, University of Quebec. He is currently working as an Engineer at Bombardier Aerospace, Montreal. His current research interests include neural networks and system identification, new methodologies for aircraft modeling and simulation, and system identification and parameter estimation in both time and frequency domains.

Ruxandra Mihaela Botez received the Bachelors degree in aerospace engineering from the Faculty of Aircraft Design, Bucharest, Romania. She received the Masters degree from the Ecole Polytechnique, Montreal, QC, Canada, on dynamic semiempirical methods for helicopters, and the Ph.D. degree from McGill University, Montreal, QC, on fluid-structure interactions and nonlinear dynamics.

She worked five years at the helicopter factory in Brasov, Romania, and at Bombardier Aerospace, Montreal, and for one year as a Post-Doctoral Fellow at Auburn University, Auburn, AL. She is now a Full Professor in the Department of Automated Production Engineering, École de Technologie Supérieure, University of Qubec, Montreal. She is a Founder and Director of the Laboratory of Applied Research in Active Controls, Avionics and Aeroservoelasticity (LARCASE), University of Qubec. The LARCASE is equipped with a Cessna Citation X aircraft simulator and a blown-down wind tunnel. The research projects of her team at LARCASE are realized in collaboration with aerospace companies such as Bombardier Aerospace, Bell Helicopter Textron, Mirabel, QC, CAE Inc., St-Laurent, QC, CMC Electronics-Esterline, St-Laurent, QC, Presagis, Montreal, NASA Dryden Research Center, Edwards, CA, and Thales Canada, Montreal. She has authored/co-authored more than 150 papers in scientific journals and conference proceedings. Her current research interests include methodologies for modeling and simulation of aircraft and helicopters and their validation using experimental wind tunnel and flight simulator data.