Artificial Neural Networks-Extended Great Deluge Model to predict Actuators Displacements for a Morphing Wing Tip System

Abdallah BEN MOSBAH[1], Ruxandra Mihaela BOTEZ*[,1], Soumaya MEDINI[2], Thien-My DAO[3]

*Corresponding author
[1]LARCASE, Department of Automated Production Engineering,
École de Technologie Supérieure, University of Quebec,
1100 Notre Dame West, Montreal, Quebec, Canada, H3C 1K3,
Abdallah.ben-mosbah@polymtl.ca, Ruxandra.Botez@etsmtl.ca*
[2]Department of Computerand Software Engineering, Polytechnique de Montréal,
University of Montréal,
2500 chemin de Polytechnique Montréal, Québec, H3T 1J4,
Soumaya.medini@polymtl.ca
[3]Department of Mechanical Engineering, École de Technologie Supérieure,
University of Quebec,
1100 Notre Dame West, Montreal, Quebec, Canada, H3C 1K3,
Thien-My.Dao@etsmtl.net

DOI: 10.13111/2066-8201.2020.12.4.2

Received: 21 September 2020/ Accepted: 30 October 2020/ To be published: December 2020

***Abstract**: Resin-based fiber composite materials have received attention in aerospace composite engineering, particularly in aircraft morphing structures, due to their high mechanical characteristics, such as stiffness, and because of their potential to highly reduce the structural mass of modern aircraft. Aircraft morphing is referred to as the ability of an aircraft's surface to change its geometry in flight. The modelling of a dynamic morphing wing system is here studied. The morphing wing was controlled using four electric actuators situated inside of the wing model. The main role of these actuators was to modify the wing upper surface shape designed and manufactured with a flexible material, so that the laminar-to-turbulent flow transition point can move closer to the wing trailing edge, thus causing a minimum viscous drag, for various flow conditions. To determine the skin deflections in the four actuators points, both LVDT and dial indicator gages were positioned on the wing. Four Linear Variable Differential Transducers (LVDTs) were used to indicate the positions of the four actuators, and four Dial Indicators gages were positioned on the wing to measure the real deflections of the flexible composite skin in the four actuation points. The relationship between the Dial Indicators' values and the LVDTs' values for a same set-point command signal had a nondeterministic and unpredictable behavior (not a linear one). The values of the displacements given by the LVDTs were different than the values given by the Dial Indicators. In this paper, an Artificial Neural Network (ANN) model was investigated created with the aim to predict the displacements of the wing upper surface skin in real time using four actuators. The proposed model was trained using the Extended Great Deluge (EGD) algorithm.*

***Key Words**: neural networks, prediction, morphing wing, optimization skin, extended great deluge*

1. INTRODUCTION

Since October 2010, the International Civil Aviation Organization (ICAO), the Canadian government and Canadian aerospace industries have been working towards a Greenhouse Gas (GHG) reduction of 17% percent below the levels observed in 2005, and an average fuel efficiency improvement of 2% (Transport Canada, Aviation Emissions, 2012). One way of achieving those goals is to produce a continuously laminar flow on the wing surface over an operating range of flow conditions characterized by Mach numbers, airspeeds, and incidence angles [1, 2]. In the aerospace vehicle field, ''wing morphing'' refers to the ability of an aircraft wing to change its shape during flight phases consisting of take-off, climb, cruise, descent and landing, thereby providing aerodynamic performance advantages at each step of the flight. The "wing morphing'' approach is referred to as the variation in a wing's shape. In this way, a "morphing wing" can be characterized as falling within three classifications: i) Wing platform alternation (wing span resizing, chord length change, and sweep angles variation); ii) Out-of-plane transformation of the wing (airfoil camber changing, lateral wing bending and twisting); or iii) Airfoil shape adjustment (reshaping of the upper and/ or lower surface of the airfoil) [3]. Detailed investigations of composite materials, and the wide range of applications in modern aeronautics have made the reshaping of a flexible upper surface composed of composite material a realistic possibility that could allow future aircraft and Unmanned Aerial Vehicles (UAV's) to fly long distances with minimum fuel consumption. Fuel efficiency requirements have emphasized the importance of improving aerodynamic efficiency through wing geometry modifications that can move the laminar-to-turbulent transition point close to the wing trailing edge, thereby reducing drag. A high number of theoretical and experimental studies on morphing wings have been developed. These studies began with work on independent aerofoils and have been extended to different airplane configurations [3]. In this paper, we focus on the last type of morphing wing definition given by Consortium for Research and Innovation in Aerospace in Quebec (CRIAQ) 7.1 project, the modification of the upper surface of the airfoil shape. The approach in this paper uses four Brushless Servo Motors to change the airfoil's upper surface, producing a drag reduction following to a modification of the laminar-to-turbulent flow transition point position. This transition point was situated as close as possible to the trailing edge of the airfoil model in order to delay the flow transition.

The Consortium for Research and Innovation in Aerospace in Québec (CRIAQ) launched the MDO-505 Morphing Architectures and related Technologies to improve the Wings Efficiency project in 2012. MDO-505's objective was to design and manufacture a morphing wing with a flexible upper surface in composite materials, controlled using electric actuators and highly specialized miniature pressure sensors. "Linear interpolation" is simple to use but is not well-suited for nonlinear modelling. "Polynomial regression" is a method used to obtain an empirical equation that predicts observed results, but it is time-consuming; and it is difficult to develop an empirical generalization to fit the experimental data by using polynomial regression. An Artificial Neural Network (ANN) model was investigated, and further created using the Matlab Neural Network toolbox, and also trained using the Extended Great Deluge (EGD) back propagation algorithm. The application of ANNs to solve engineering problems has received increasing interest during recent years because of their ability to learn and generalize complex, multivariate, multidimensional and nonlinear relationships by training using sample data that contain noisy or incomplete information. ANNs also have a clear advantage because of the fact that a multilayer neural network can describe experimental data with fewer numbers of iterations and less computation time per iteration. The proposed ANN model was designed in this paper to be integrated in the control loop of the actuators used to deform the morphing wing upper surface skin. For a good precision, a robust controller is essential. Authors in [4, 5] proposed and validated a closed-loop controller for a morphing wing model. The same authors proposed an open-loop control system to validate a morphing wing model [6]. Authors in [7, 8] proposed a control system based on a combination of Proportional-Integral (PI) and bi-positional laws optimum, and used it in the control of a morphing wing model. Another controller based on On/ Off Proportional-Integral (PI) methodology developed in [9, 10] was tested and validated experimentally.

Neural Networks are used in various fields such as classification problem, control or manufacturing [11 to 16], an example is the aerodynamic coefficients estimations [17] and calibration of wind tunnels [18]. Authors in [16] developed a wind velocity control for a low-speed wind tunnel based on ANNs and fuzzy logic hybridization. Another type of hybridization was presented in [19], in which they proposed a controller for a Smart Material Actuator (SMA) based on an Adaptive Neuro-Fuzzy Inference System (ANFIS). ANNs were used in [20] to design a model for fault detection in aircrafts. ANNs have also been used to develop identification and prediction models to calculate and predict aerodynamic coefficients [21, 22, 23]. Authors in [24] used ANNs to design controllers for autopilot systems. Many other detection and identification models are presented in [25, 26, 27].

The motivation in this work is the finding of a numerical description of the non-linear relationships between the Linear Variable Differential Transducer's (LVDT) values and the Dial Indicator gauge's values that allowed the validation of simulated airfoils using ANN-EGD methodology. The Xfoil software combined with a real time optimization of the morphing wing in the Wind Tunnel Tests (WTTs) with the aim to validate the whole morphing system.

2. MORPHING WING PROJECT

2.1 Morphing wing model

The objective of this paper is to validate a morphing wing's ability to improve aircraft aerodynamic performance. The morphing wing model was designed based on a real airplane wing-tip model. This wing-tip was not equipped with a winglet; it was composed of a wing and an aileron. The reference wing was manufactured from aluminum; its upper surface (from 20% to 65% of the chord) was then replaced by a morphing skin optimized and manufactured from different composite materials. A mechanical actuator system was fixed inside the wing to modify the wing shape. Four actuators were designed and manufactured to achieve the desired skin deformations. The four actuators were fixed directly on two ribs at 32% and 48% of the chord (two actuators on each line); the mobile parts of the actuators were fixed on the morphing part of the wing with the aim to attain the expected skin deformations. The wing model was also equipped with a rigid aileron, and later, with an adaptive morphing aileron. The rotation centers of these ailerons were located at 72 % of the chord. The rigid and adaptive ailerons installed on the wing were used during three sets of Wind Tunnel Tests (WTTs). Their geometrical characteristics and the airfoil of the wing model are presented in Figures 1 and 2.

This paper shows research methodologies and results obtained in the CRIAQ MDO 505 project. This project was realized following a collaborative international effort among participants in Canada and in Italy, representing academia, industry and government agencies. The participants in Canada were teams from Bombardier Aerospace, Thales, the École de Téchnologie Supérieure, and the École Polytechnique de Montréal. The Italian participants were teams from the University of Naples Federico II (Italy), the Italian Aerospace Research Center CIRA, and Alenia Aeronautica. He project was funded by the industrial participants as well as by the Consortium de Recherche et d'Innovationen Aérospatiale au Québec (CRIAQ) and Natural Sciences and Engineering Research Council of Canada (NSERC). The wind tunnel tests on the full wing-tip were done at the National Research Council- Institute of Aerospace Research of Canada's (NRC-IAR).

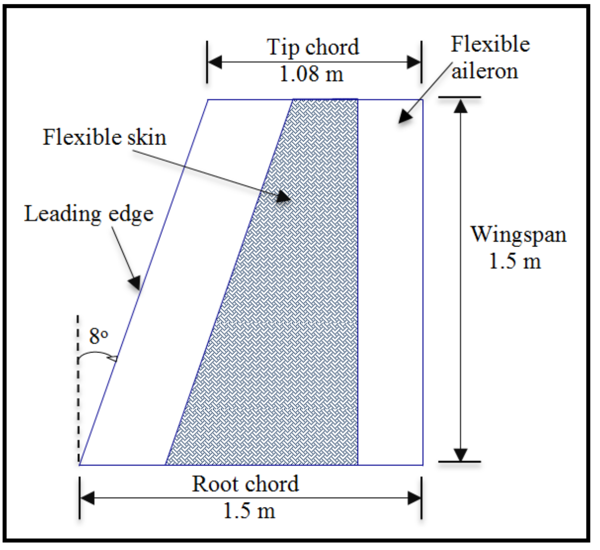


Fig. 1 CRIAQ MDO 505 Morphing Wing

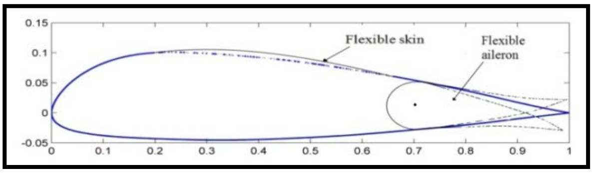


Fig. 2 CRIAQ MDO 505 Morphing Wing Profile

The CRIAQ MDO505 project involved the theoretical and numerical determination of optimized airfoils needed to maintain laminar flow over the upper wing surface for different flight conditions by means of 2D and 3D simulations using CDF software (Xfoil and Fluent). Each simulated airfoil represented the shape that the flexible skin has to achieve by using the four actuation points. The next step of the project is to design of the actuation control system for the four linear actuators that reshape the composite skin into the simulated optimized airfoil within an error displacement under 4 thousandth of an inch (0.1 mm).

Two architectures were considered to control the morphing wing's skin, using open and closed loop methodologies; these architectures are next explained. An open loop control commanded the four actuators inside the wing until the theoretical airfoil's shape was obtained. Four dial indicators placed outside the wing measured the real skin's displacement, and four LVDT sensors measured the displacements of the actuators' rods. Each airfoil had its four LVDT values corresponding to experimental actuators displacements as above mentioned, validated by the dial indicators shown on Fig.3. During the wind tunnel tests, real time pressure data signals provided by the 32 XCQ-062-5D Kulite sensors placed over the wing's upper surface were recorded to determine if any experimental relationship could be found between the dial indicators and the LVDT measured sensors values. Fig. 4 shows the wing's installation during the wind tunnel tests that was done on April 2015 at the National Research Council's NRC-IAR in Ottawa.

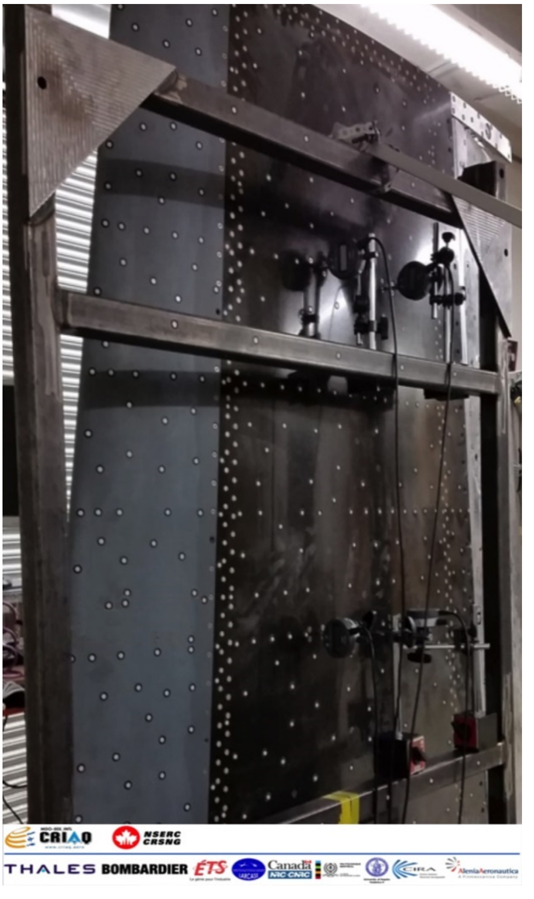


Fig. 3 Airfoil validation by dial indicators

Fig. 4 Open loop control test at the NRC-IAR subsonic wind tunnel

For the closed loop, pressure feedback from the 32 Kulite sensors were taken into account to displace the composite skin to a desired airfoil shape. In this set up, it was not possible to use an LVDT dial indicator correspondence tracking database because, in a real-time closed loop, the skin displacement responded only to the specific flow conditions over the wing's surface. Given that there was not found a linear relationship between the Linear Variable Differential Transformers (LVDTs) and the upper surface of the wing, there was no way to be certain if the desired skin's position has been reached, and thus the wind tunnel tests results could be compromised.

2.2 Instrumentation

The Data Acquisition System used was a 24-bit analog-to-digital converter with four NI PXIe-4330 modules, able to simultaneously sample 32 analog input channels (Kulite pressure sensors) at 20 kHz. This data acquisition system is compatible with Matlab Simulink program codes. The 32 Kulite sensors, capable of measuring differential pressures, are suited for both dynamic and static pressure measurements in wind tunnel applications. These sensors are mounted on the wing's upper surface. Each XCQ-062 sensor can measure pressures up to 5 PSI with an accuracy of ± 0.025 PSI, has a bandwidth up to 20 KHz suitable for flow transition measurement, has a housing of 0.066 inches in diameter, and a weight of 0.2 grams. Four very compact (5-inch housings) and 1500N push/pull force linear actuators were custom (in-house) made at the LARCASE. All the instrumentation inside the morphing wing is shown on Fig. 5. The CRIAQ MDO505 project used the NRC–IAR's (National Research Council – Institute for Aeronautical Research) subsonic 2 × 3 meters Wind Tunnel, with a maximum airspeed of 140 m/s, and a turbulence level of 0.13%, for validation of numerical results.

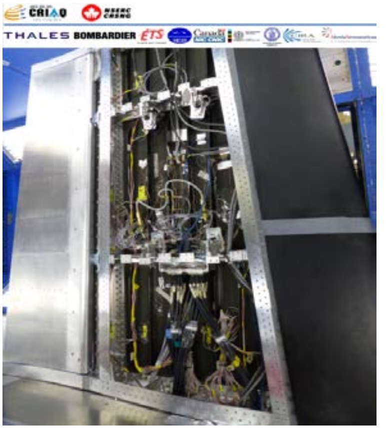


Fig. 5 Sensors inside the morphing wing

3. EXTENDED GREAT DELUGE OPTIMIZER

A meta-heuristic algorithm, called the Extended Great Deluge (EGD) algorithm, was used to optimize and train the Neural Network model. This algorithm was introduced in [28]. The EGD algorithm has been utilized to resolve different problems such as timetabling [28], optimization of manufacturing cell formation and scheduling [29, 30], optimization of neural networks for calculation of aerodynamic coefficients [17], as well as in Wind Tunnel calibration [18]. The EGD algorithm has shown a very good performance. As described in [28], the steps of EGD algorithm are:

-Initialization of the solution S
-Calculation of the objective function $f(S)$
-Initialization of the limit $B= f(S)$
-Specification of the parameter ΔB
-While the stop condition is not satisfied, do

- Define the neighborhood $N(S)$
- Select randomly the solution $S^{*} \epsilon\ N(S)$
- If ($f(s^*) \leq f(s)$) or ($f(s^*) \leq B$)
  - Accept S^*
  - $B=B- \Delta B$

- End *if*

-End of while.

4. ANN-EGD ALGORITHM

The EGD algorithm was used to optimize the number of neurons in each layer. The optimization process is normally required in order to obtain a robust and optimal neural network, and to minimize the output error as much as possible. The *objective function* used in the process of training and optimization was the Mean Squared Error (MSE), expressed as follows:

$$MSE = \frac{1}{N}\sum_{i \in N}(x_i - y_i)^2$$

where x_i are the desired values, y_i are the predicted values of the Neural Networks and N is the number of the training data points. To use the EGD algorithm, we need to specify the neighborhood research method to find a solution for this problem. The optimal neural network configuration was investigated using testing solutions by performing changes in the motions in neighborhoods of solutions with a minimal modification. To limit the neural network execution time and thus to avoid the need to use a high number of neurons, the maximum number of neurons was limited to 10 neurons per layer. The neighborhood algorithm is given below [31]:

1) Initialization of a number of layers at 1;
2) Random selection of a number of neurons between 1 and 10;
3) Training and testing of the network;
4) Number of layers=Number of layers + 1; and
5) If the number of iterations has not been reached, then one layer is chosen randomly and algorithm continues from step 2).

5. DESIGN OF AN ANN-EGD PREDICTION SYSTEM

The objective of this study was to design a prediction system model based on ANNs methodologies with the aim to predict the deformation of CRIAQ MDO505 project's carbon skin using an actuator system. This system is composed of four different ANN-EGDs algorithm, one for each actuator. The input parameters are the LVDT's displacements and the outputs are the displacement values of the upper surface of the wing (Fig. 6). A huge database of LVDT's and dial indicator values was created for simulation purposes. 161 cases were used for the learning phase and 24 for the variation testing phase. Using the EGD algorithm, in the optimization phase found the optimal configuration of our ANN model was found. The architectures of the proposed neural networks for each actuator are presented in Tables 1 to 4.

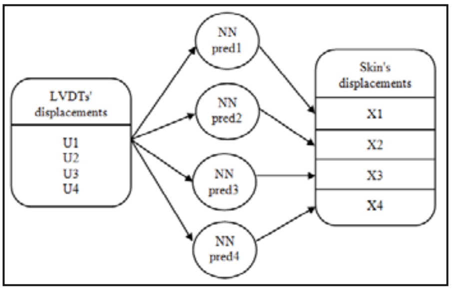


Fig. 6 Prediction system

Table 1. Neural Network architecture for actuator number 1

Layer number	Number of neurons	Transfer function
1	6	Tangent sigmoid
2	5	
3	10	
4	5	
5	4	

Table 2. Neural Network architecture for actuator number 2

Layer number	Number of neurons	Transfer function
1	10	Tangent sigmoid
2	6	
3	9	
4	6	
5	2	

Table 3. Neural Network architecture for actuator number 3

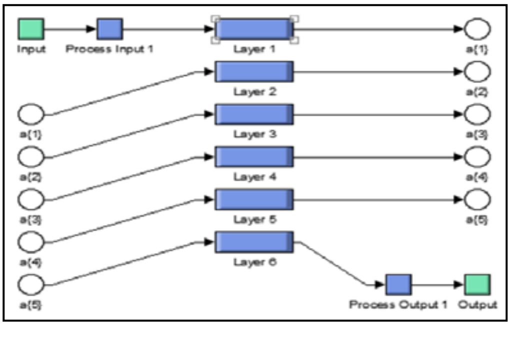
Layer number	Number of neurons	Transfer function
1	5	Tangent sigmoid
2	7	
3	7	
4	7	
5	6	

Table 4. Neural Network architecture for actuator number 4

Layer number	Number of neurons	Transfer function
1	5	Tangent sigmoid
2	9	
3	10	
4	6	
5	10	

6. VALIDATION RESULTS

The ANN models were converted using *Matlab/ Simulink* blocks for the open loop control. The Simulink model architecture of the first of the ANN-EGD prediction models is presented in Fig. 7.



7. Simulink model of a neural network

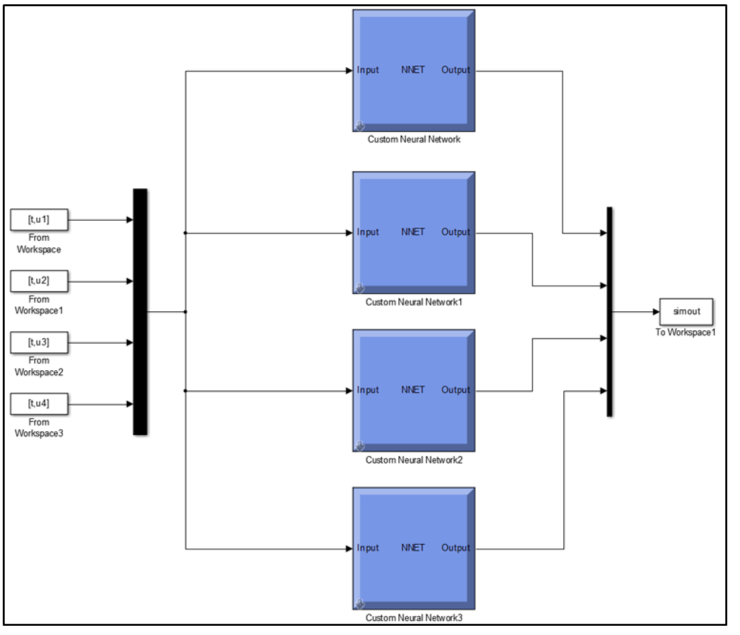


Fig. 8 General model of our system

The variable $a(i)$ corresponds to the outputs of *Layer i*, and to the inputs of Layer i+1.The *Inputs* correspond to the *LVDT* values, and the *Outputs* are the prediction values. Finally, a general Simulink model is obtained, as displayed in Fig. 8.

In order to validate the proposed ANN models, new measurements of the LVDT values and dial indicators were used; their values are different than those used earlier. The dial indicator values were used as inputs in the general model.

The prediction LVDT displacements were compared to the LVDT measurements, and then the difference (comparison) between the predicted and the measured deformation values for all actuators were realized in a visual display. These results are presented in Figures 9, 10, 11 and 12.

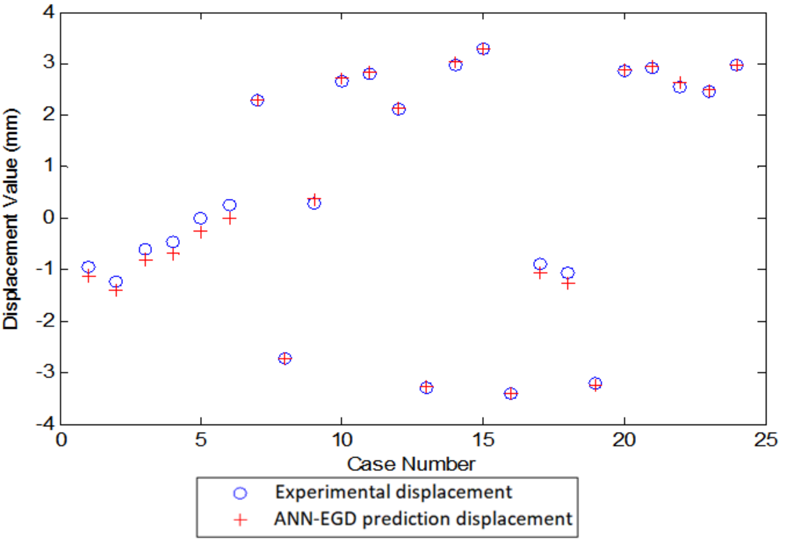


Fig. 9 Experimental and predicted displacements for actuator 1

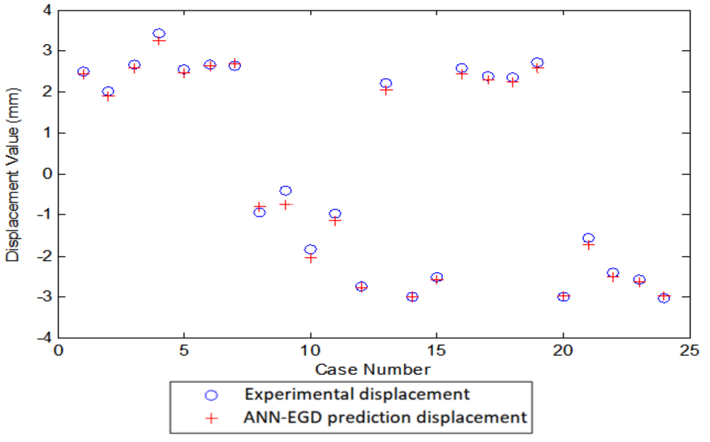


Fig. 10 Experimental and predicted displaments for actuator 2

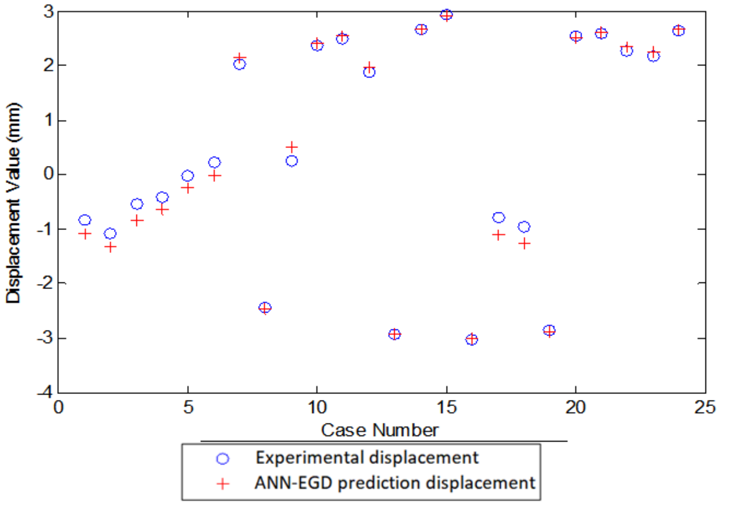


Fig. 11 Experimental and predicted displaments for actuator 3

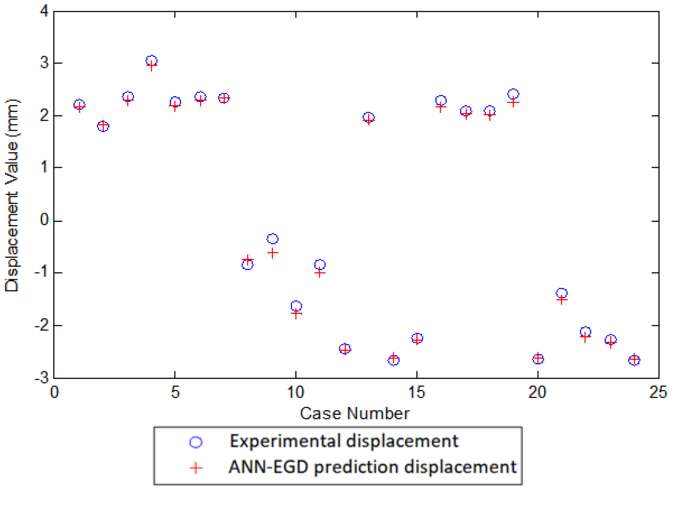


Fig. 12 Experimental and predicted displaments for actuator

It can be observed that there is only a minimal difference between the experimental and the predicted values; the average difference between the ANN-EGD predicted values and the experimental displacements did not exceed 0.08 mm. The mean errors for each ANN-EGD prediction model are presented in Table 5.

Table 5. Mean errors between experimental and predicted values

Mean error (mm)			
Actuator 1	Actuator 2	Actuator 3	Actuator 4
0.05	0.08	0.06	0.06

7. CONCLUSIONS

In this research, a Neural Network Model optimized and trained using the EGD algorithm was proposed to be implemented in the control loop of four actuators; this loop was used to change the morphing wing model shape in the CRIAQ MDO-505 project. The proposed model was tested, and further validated using experimental data. Four Neural Networks algorithms were used, one for each actuator, the obtained results were very good because of the fact the prediction of the displacements was found to be very close to the displacements obtained using Dial Indicators gauges.

ACKNOWLEDGEMENTS

Special thanks are dues to the team of the CRIAQ MDO 505 project, for their support in this project, in particular to Mr Philippe Molaret, Mr Xavier Louis and Mr Bernard Blouin from Thales, as well as to MrFassiKafyeke and Mr Patrick Germain from Bombardier Aerospace. We would like to thank, for the financial support to this project, to the Bombardier and Thales teams, as well as to the Consortium de Recherche et d'Innovationen Aérospatiale au Québec (CRIAQ) and Natural Sciences and Engineering Research Council of Canada (NSERC) organizations.

REFERENCES

[1] J. D. Jacob, On the Fluid Dynamics of Adaptive Airfoils, *Proceedings of 1998 ASME International Mechanical Engineering Congress and Exposition,* American Society of Mechanical Engineers, Fairfield, NJ, pp. 1–10, 15–20 November 1998.

[2] D. W. Zingg, L. Diosady and L. Billing, Adaptive Airfoils for Drag Reduction at Transonic Speeds, *24th Applied Aerodynamics Conference,* AIAA Paper 2006-3656, pp. 1–15, 5–8 June 2006, Reston, Virginie.

[3] A. Y. N. Sofla, S. A. Meguid, K. T. Tan and W. K. Yeo, Shape Morphing of Aircraft Wing: Status and Challenges, *Materials and Design*, vol. **31**: pp. 1284-1292, 2010.

[4] A. V. Popov, T. L. Grigorie, R. M. Botez, M. Mamou and Y. Mebarki, Closed-Loop Control Validation of a Morphing Wing Using Wind Tunnel Tests, *Journal of Aircraft,* vol. **47**, no. 4, pp. 1309-1317, 2010.

[5] A. V. Popov, M. Labib, J. Fays and R. M. Botez, Closed loop control simulations on a morphing laminar airfoil using shape memory alloys actuators, *AIAA Journal of Aircraft,* vol. **45**. No. 5, pp. 1794-1803, 2008.

[6] A. V. Popov, T. L. Grigorie, R. M. Botez, Y. Mébarki and M. Mamou, Modeling and testing of a morphing wing in open-loop architecture, *AIAA Journal of Aircraft,* vol. **47**, no. 3, pp. 917-923, 2010.

[7] T. L. Grigorie, A. V. Popov, R. M. Botez, M. Mamou and Y. Mebarki, A morphing wing used shape memory alloy actuators new control technique with bi-positional and PI laws optimum combination. Part 1: design phase, 7th *International Conference on Informatics in Control, Automation and Robotics ICINCO,* Funchal, Madeira, Portugal, 15-18 June 2010.

[8] T. L. Grigorie, A. V. Popov, R. M. Botez, M. Mamou and Y. Mebarki, A morphing wing used shape memory alloy actuators new control technique with bi-positional and PI laws optimum combination. Part 2:

experimental validation, *7th International Conference on Informatics in Control, Automation and Robotics ICINCO* 2010, Funchal, Madeira, Portugal, 15-18 June 2010.

[9] T. L. Grigorie, A. V. Popov, R. M. Botez, M. Mamou, Y. Mébarki, On-off proportional-integral-controller for a morphing wing. Part 1: Actuation mechanism and control design, *Proceedings of the Institution of Mechanical Engineers, Part G, Journal of Aerospace Engineering*, vol. **226**, no.2, pp. 131-145, 2012.

[10] T. L. Grigorie, A. V. Popov, R. M. Botez, M. Mamou and Y. Mébarki, On-off proportional-integral-controller for a morphing wing. Part 2: Control validation-numerical simulations and experimental tests, *Proceedings of the Institution of Mechanical Engineers, Part G, Journal of Aerospace Engineering*, vol. **22**, no.2, pp.146-162, 2012.

[11] B. K. Wrong, S. L. Vincent and J. Lam, A bibliography of neural network business applications research: 1994–1998, *Computers and Operation Research*, vol. **27**, pp.1045–1076, 2002.

[12] K. J. Hunt, D. Sbarbaro, R. Zbikowski and P. J. Gawthrop, Neural networks for control systems – a survey, *Automatica*, vol. **28**, pp. 1083–1112, 1992.

[13] G. J. Udo, Neural networks application in manufacturing process, *Computers and Industrial Engineering*, vol. **23**, no.1–4, pp. 97–100, 1992.

[14] B. K. Wong, T. A. Bodnovich and Y. Selvi, Neural network application in business: a review and analysis of the literature (1988–1995), *Decision Support Systems*, vol. **19**, pp.301–320, 1997.

[15] D. Chen and P. Burrel, On the optimal structure design of multilayer feedforward neural networks for pattern recognition, *Int. J. Pattern Recognition and Artif. Intell*, vol. **6**, no. 4, pp. 375–398, 2002.

[16] C.-Z. Xuan, Z. Chen, P. Wu, Y. Zhang and W. Guo, Study of Fuzzy Neural Network on Win Velocity control of Low-Speed Wind Tunnel, *International Conference on Electrical and Control Engineering*, Wuhan, China, pp. 2024 – 2027, 2010

[17] A. Ben Mosbah, R. Botez, and T. M. Dao, New methodology for calculating flight parameters with neural network - EGD method, *AIAA Modeling and Simulation Technologies (MST) Conference*, Boston, MA, USA, August 2013.

[18] A. Ben Mosbah, S. M. Flores, R. Botez. and T. M. Dao, New Methodology for Wind Tunnel Calibration Using Neural Networks - EGD Approach, *SAE Int. J. of Aero.*, vol. **6**, no.2, pp.761-766, 2013.

[19] T. L. Grigorie, R. M. Botez, Adaptive neuro-fuzzy inference system based controllers for smart material actuator modeling, *Proceedings of the Institution of Mechanical Engineers, Part G., Journal of Aerospace Engineering*, vol. **223**, no. 5, pp. 655-668, 2009.

[20] H. E. Rauch, R. J. Kline-Schoder, J. C. Adams and H. M. Youssef, Fault detection isolation and reconfiguration for aircraft using neural networks, *AIAA Paper*, 3870, 1993.

[21] D. J. Linse and R. F. Stengel, Identification of aerodynamic coefficients using computational neural networks, *Journal of Guidance. Control and Dynamics*, vol. **16**, no.6, pp. 1018–1025, 1993.

[22] R. Wallach, B. S. De Mattos and R. Da Mota Girardi, Aerodynamic coefficient prediction of a general transport aircraft using neural network, *25th International Congress of the Aeronautical Sciences ICAS* 2007.

[23] A. Ben Mosbah, R. Botez, T. M. Dao, New methodology for calculating flight parameters with neural network - EGD method, *AÉRO 13, 60th Aeronautics Conference and AGM*, 30 April - 2 May 2013, Toronto, Canada.

[24] M. R. Napolitano and M. Kincheloe, On-line learning neural network controllers for autopilot systems, *Journal of Guidance Control and Dynamics*, vol. **33**, no.6, pp. 1008–1015, 1995.

[25] M. D. Johnson and K. Rokhsak, Using artificial neural network and self-organizing maps for detection of airframe icing, *Journal of Aircraft*, vol. **38**, no.2, pp. 224–230, 2001.

[26] R. Aykan, Kalman filter and neural network-based icing identification applied to A340 aircraft dynamics, *Aircraft Engineering and Aerospace Technology: An International Journal*, vol. **77**, no.1, pp. 23–33, 2005.

[27] M. D. Johnson and K. Rokhsaz, Using artificial Neural networks and self organizing maps for detection of airframe icing, *Atmospheric Flight Mechanics Conference*, AIAA-2000-4099, 2000.

[28] E. Burke, Y. Kov, J. Newell, S. Petrovic, A time-predefined local search approach to exam timetabling problems, *IIE Transactions*, vol. **36**, no. 6, pp. 509–528, 2004.

[29] A. Ben Mosbah, T. M. Dao, Optimimization of Group Scheduling Problem Using the Hybrid Meta-heuristic Extended Great Deluge (EGD) Approach: A Case Study, *The Journal of Management and Engineering Integration*, vol. **4**, no.2, pp. 1-13, 2011.

[30] A. Ben Mosbah and T. M. Dao, Optimization of Manufacturing Cell Formation with Extended Great Deluge Meta-heuristic Approach, *International Journal of Services Operations and Informatics*, vol. **7**, no.4, pp. 280-293, 2013.

[31] A. Ben Mosbah, R. Botez and T. M. Dao, New Methodology for the Calculation of Aerodynamic Coefficients on ATR-42 Scaled Model with Neural Network-EGD Method, *The ASME 2014 International Mechanical Engineering Congress & Exposition*, At Montreal, Quebec, Canada, 2014.