PROCEEDINGS OF SPIE

SPIEDigitalLibrary.org/conference-proceedings-of-spie

Studying the effect of current on an electric-powered ducted fan using artificial neural networks

Faroukh, Yousuf , Berrim, Lina , Al-Shabi, Mohammad, Gadsden, S. Andrew , Wilkerson, Stephen

Yousuf Faroukh, Lina Berrim, Mohammad Al-Shabi, S. Andrew Gadsden, Stephen A. Wilkerson, "Studying the effect of current on an electric-powered ducted fan using artificial neural networks," Proc. SPIE 10979, Energy Harvesting and Storage: Materials, Devices, and Applications IX, 109790K (13 May 2019); doi: 10.1117/12.2522983

Event: SPIE Defense + Commercial Sensing, 2019, Baltimore, Maryland, United States

Studying the Effect of Current on an Electric-powered Ducted Fan using Artificial Neural Networks

Yousuf Faroukh[a], Lina Berrim[a], Mohammad Al-Shabi[a,1], S. Andrew Gadsden[b], and Stephen A. Wilkerson[c]

[a] College of Engineering, University of Sharjah, Sharjah, United Arab Emirates

[b] College of Engineering and Physical Sciences, University of Guelph, Ontario, Canada

[c] York College of Pennsylvania, York, Pennsylvania, USA

ABSTRACT

In this paper, an experimental study is performed to find the relation between the current of a battery and the power thrust of an electric-powered ducted fan. Electric-powered duct fans are becoming increasingly popular in unmanned aerial vehicles (UAVs) and are controlled by a pulse position modulation controller. Three different measurements are taken by three transducers, namely: a multimeter with a range of 0 to 400 DC Amps that measures the input current feeding the electric speed controller from the batteries; a load cell with a range of 0 to 45 KG to measure the thrust output of each of the motor; and, a thermocouple to measure the temperature of the Li-Po batteries. Once the data was obtained, an artificial neural network was trained and tested to obtain the relationship between the input (pulse position modulation) and output (the thrust). The effects of battery current on an electric-powered ducted fan are then summarized.

Keywords: EDF, ANN, Current, Thrust, PPM, Li-PO battery.

1. INTRODUCTION

Artificial intelligence (AI) is the field of computer science devoted to algorithms that are capable of mimicking living beings. One of the main algorithms used in artificially intelligent systems is known as an artificial neural network (ANN). It follows the same data processing methodology that the human brain uses [1]. For example, when we look at an object, for instance a car, we know that the object is a car regardless of its color or shape, because specific neurons in a certain area of our brain (occipital lobe) has come across a similar shape from previously obtained knowledge, where we have learned to associate that an objects is identified as a car if it has four wheels and chairs [2]. ANN consists of blocks called 'neurons' that are connected together in levels, which are called layers, through weights. This structure allows to identify the relationship between the input-output pattern, like the car example [2,3], where any new data is predicted through high nonlinear interpolation/fitting relations [3-6]. ANNs gather their information by observing patterns and relationships in data that are pre-supplied by the system professional. After that, ANN trains the internal weights to obtain the memory and relations. The result is an intelligent system gifted with learning, prediction, and recognition of objects and coming up with problem solving solutions. This is how Artificial Neural Networks operate in a brief. Artificial Neural Networks have a wide spectrum of applications in machine learning. For instance, one of the most common application of ANN's in the medical field is disease diagnosis [7-10]. On another hand, it is widely used in other applications including the major application of this research, Unmanned air Vehicle (UAV) [11-17].

Unmanned aerial vehicles have attracted a number of researchers in the last decade due their wide applications in agricultures [18-19], military [20], and civilian applications [21]. In this paper, UAV is considered specially the ones that use Electric ducted fans (EDFs). The EDF input is the current that is provided by the controller. The controller draws the current from the batteries after receiving a signal from the pulse position modulation (PPM) set by the user. The current, thrust and PPM are monitored, and their signals are collecting. These are then analyzed using Artificial Neural Network (ANN) algorithm to define the relation between them. Two ANN systems are developed in this paper: one to find a relation between PPM and current, and the other one to find the relation between current and thrust. These relations can be used later to have a better understanding of the EDF, which results in obtaining a better controller, hence, better performance.

[1] Corresponding Author, email: malshabi@sharjah.ac.ae

Energy Harvesting and Storage: Materials, Devices, and Applications IX, edited by Palani Balaya, Achyut K. Dutta, Proc. of SPIE Vol. 10979, 109790K · © 2019 SPIE
CCC code: 0277-786X/19/$18 · doi: 10.1117/12.2522983

The rest of the paper is organized as follows: Section 2 is dedicated for the methodology. This includes the data, the ANN and the bench setup. Sections 3 and 4 are dedicated to the results and discussion, and the conclusion, respectively.

2. METHODOLOGY

In this section, the ANN is used to describe the relationship between the PPM and the current, and between the current and the thrust for an EDF system. At the beginning, the user sends a command to the EDF controller as PPM signal. The controller then starts to draw current from the batteries and provide them to the EDF. EDF converts the electrical energy to mechanical energy; the propellers start to rotate. This will produce a force, referred to as Thrust, which can be used to lift an object.

2.1 Data sources and pre-processing

The experimental data used to build the ANN is obtained from an EDF bench that is illustrated in Fig. 1. Several instruments and transducers are used to obtain the data which includes the PPM, the current, and the thrust. These are illustrated in Fig. 2 and as follows:

Figure 1. The experimental bench setup

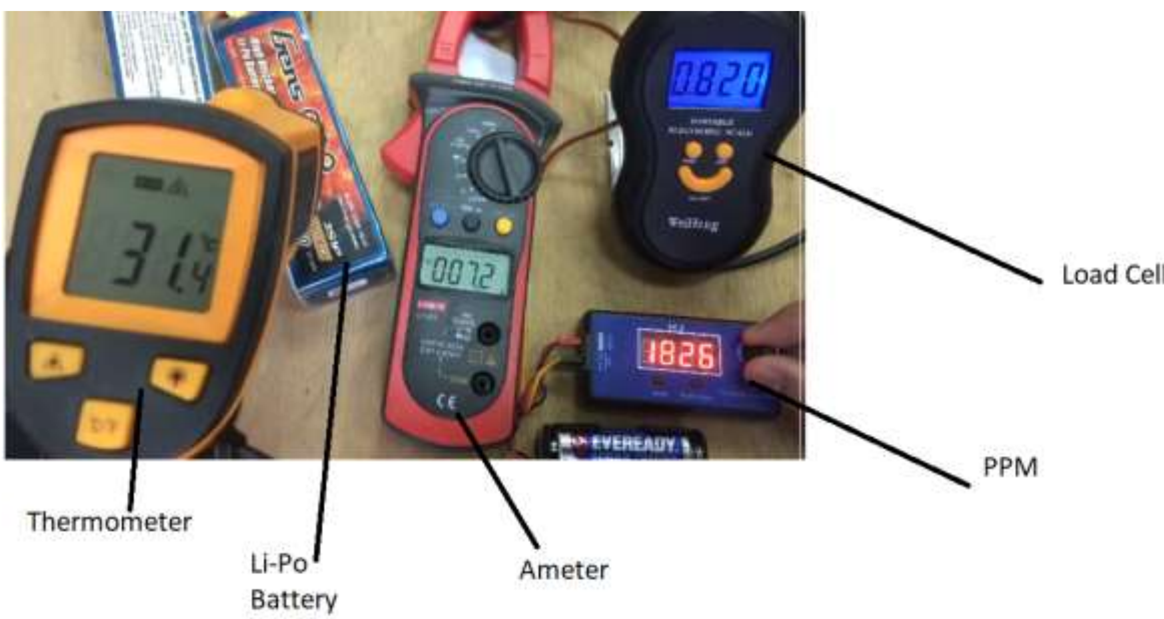

Figure 2. Instruments and transducers that are used to obtain the current, thrust and PPM

- HX711 load-cell module: It has an internal 1000 Ohm half-bridge strain gauge load cell. It has a range of 0-50kg. The output resistance is later sent to the HX711 weighing module that converts the output resistance to kilograms and feeds the data into the ARDUINO.
- MAX471 Current measurement module: It is a current measuring sensor used to measure the DC current being drawn from the batteries. The module has a range of 0-25 volts and 0-3 Amps. Our data has been scaled down using an OP-AMP circuit from a Uni-t UT203 Clamp Multimeter, which is able to measure DC currents from 0 to 400 Amps. The reading is then fed to the ARDUINO.
- PPM: It is a signal modulation that transmits pulses to the controller. The pulses have the same magnitude and width. However, the delay between the pulses vary. Shorten the delay between pulses gives an indication of high control signal, while larger delay period gives an indication of small control signal [22].
- Arduino UNO microcontroller: an Arduino UNO model R3 microcontroller has been used to collect from the previous devices.

2.2 Electric Ducted Fan

The thrust is generated using an EDF of the type JP Hobby 12-S 120mm full aluminum body and propeller. The motor used to operate the fan is a brushless 12 poles DC motor and an 8mm driveshaft connected to the fan. The motor dimensions are as follows; 42mm in diameter and 50mm in length. The motor is rated as 760 KV (KV being the no-load rotational velocity of a motor per unit Volt of input RPM/V) [23]. In regard to the propelling fan, there are 12 blades with a diameter of 120 mm. The combination of the motor and fan will produce a maximum thrust of 8 kg. The mass of the EDF unit is 693 grams including the motor, fan, and fan housing.

2.3 Batteries

LiPo Batteries (lithium-ion) are used in this research. These batteries are known to have high energy-density, yet very light in terms of mass, which is considered as an optimal power source for small aircraft propulsion [21]. There are three primary values that describe a LiPo Battery [24]:

- Energy storing capacity, in units of milliamp hour [mAh]
- Number of cells, No.-S, LiPo battery cells have a nominal voltage of 3.7 volts per cell. For example, a 3-S battery has 3 cells which outputs 11.1 Volts.
- C-rating, The C-Rating is a measure of how quickly electricity can be discharged from the battery. To determine the maximum continuous discharge that the battery is capable of, the capacity in AMPS is multiplied by discharge C-Rating. For example, a battery having a capacity of 6000 mAh and a discharge rate of 30C, has a maximum continuous discharge of 180 Amps [24].

Knowing what batteries in general are described by, the batteries that are used in this paper have 12-S with output voltage of 44.4 DC volts, a capacity of 5300 mAh, and a C-Rating of 30 C.

2.4 Electric Speed Controller

The electronic speed controller (ESC) is an electronic circuit that is used to change the speed of an electric motor by regulating the voltage that is applied to the motor. Furthermore, the ESC regulates the voltage by manipulating the pulse position modulation signal it receives from the user. The ESC that is used in this paper is a JP Hobby Mantis 120 Amps ESC [25]. The PPM signal can be generated manually or through Arduino.

2.5 ANN

ANN is applied in several applications, i.e. modeling approximation, pattern classification, optimization, control etc. [1, 27-32]. As mentioned before, ANN consists of a set of neurons, see figure 3, which work together to perform a specific task. Each neuron has multiple inputs and a single output element. These inputs are combined linearly using certain weights. An activation function is then used to deduct the output from the fused inputs. The ANN consists of input, output and one or more hidden layers. Based on the layer number, ANN can be classified to single layer perceptron, and multilayer perceptron.

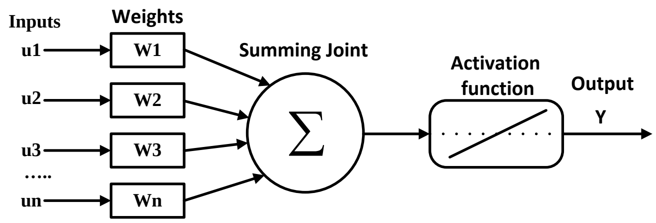

Figure 3. Neuron structure

Number of hidden layers and their neurons should be selected carefully: Small number of neurons may not be suitable to estimate the function or do the required task. Large number of neurons causes large computational time, and may result in overfitting. Therefore, the maximum number of neurons in each layer was set to 10, and the maximum number of hidden layers was set to 2. All possibilities are checked to find the best combinations. Back propagation (BP) with the Levenberg Marquardt algorithm is used to train the ANN. The training algorithm, hence, the performance highly depends on the initial selection of the weights and biases. To remove this factor, each model is trained 100 times and the best performance is selected.

The selection of ANN depends on the coefficient of determination (R^2) in the training part, and on the root mean squared error (RMSE) in selecting the best model.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(O_{actual,i}^{Norm} - O_{obtained,i}^{Norm}\right)^2}{\sum_{i=1}^{N}\left(O_{actual,i}^{Norm} - \bar{O}_{actual,i}^{Norm}\right)^2}, i = 1,2 \quad 1$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(O_{actual,i}^{Norm} - O_{obtained,i}^{Norm}\right)^2}, i = 1,2 \quad 2$$

where $O_{actual,i}^{Norm}$ and $O_{obtained,i}^{Norm}$ are the normalized actual and estimated output vector, respectively. $\bar{O}_{actual,i}^{Norm}$ is the average of the normalized output i.

3. RESULTS AND DISCUSSIONS

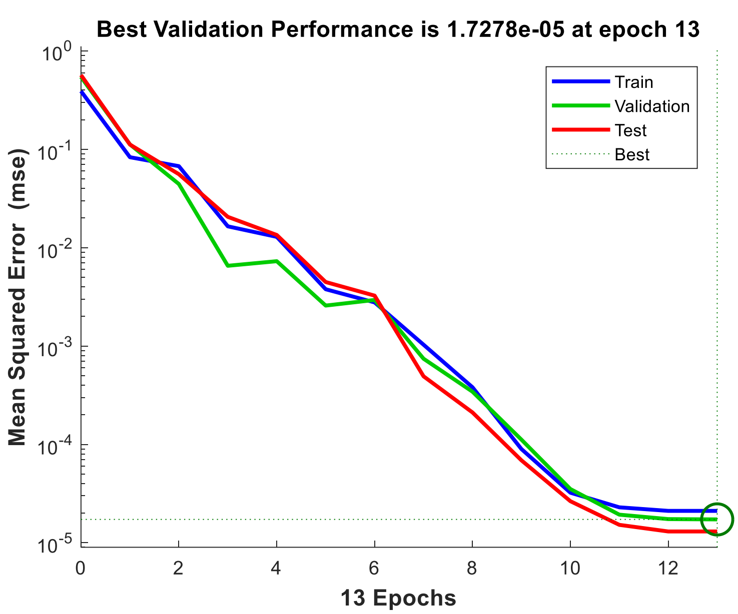

Figure 4. ANN performance for the model between the throttle and current.

Two ANN models are developed in this work; one to define the relation between PPM and current, the other one to define the relation between current and thrust. A comprehensive study is conducted in this research dedicating for one and two hidden layers. The results show that the first model consists of two layers; the first layer has five neurons, and the second layer has four neurons. The second model between current and thrust consists of two layers; the first layer has four neurons, and the second layer has six neurons. Results are shown in figures 4-11.

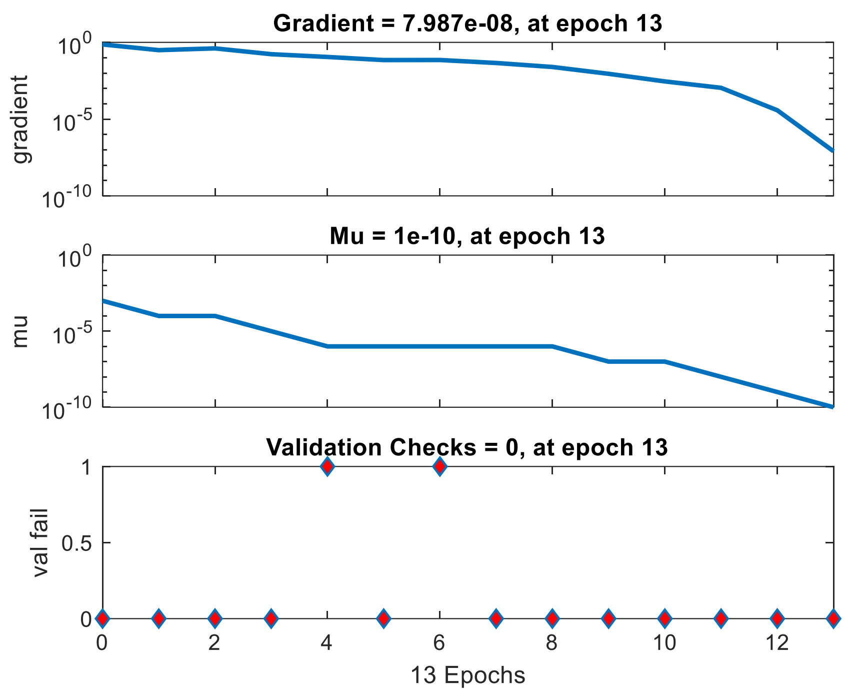

Figure 5. ANN parameters for the model between the throttle and current.

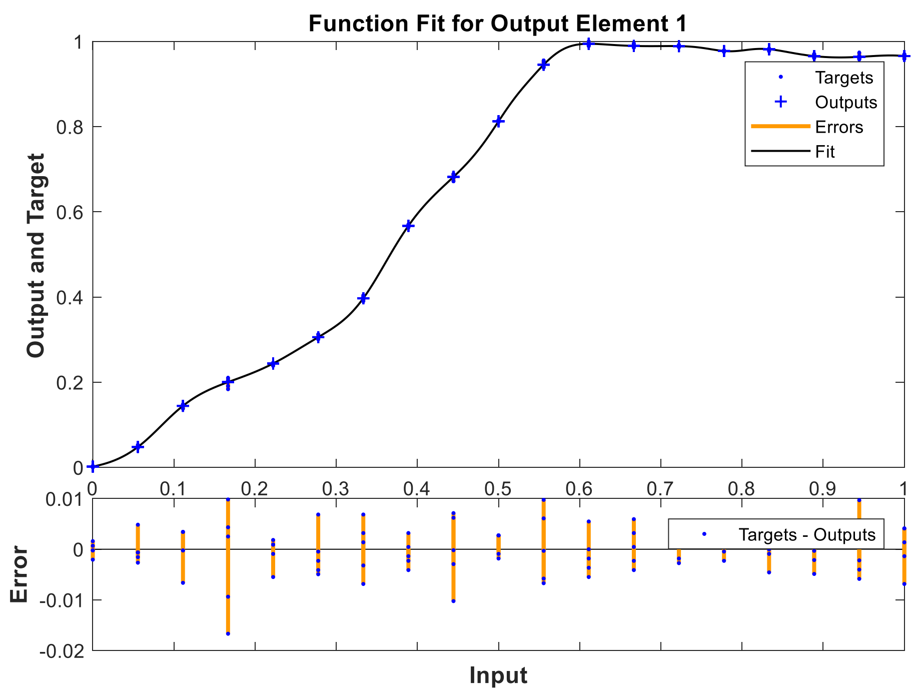

Figure 6. ANN's normalized Output and error for the model between the throttle and current.

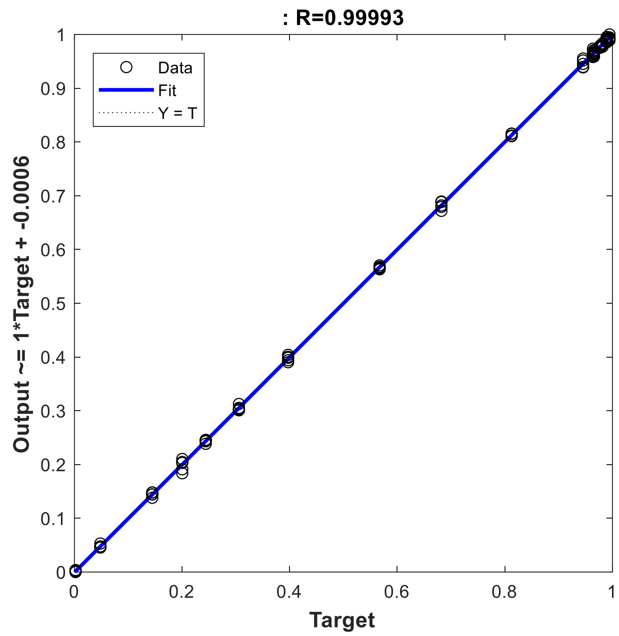

Figure 7. ANN's normalized regression for the model between the throttle and current.

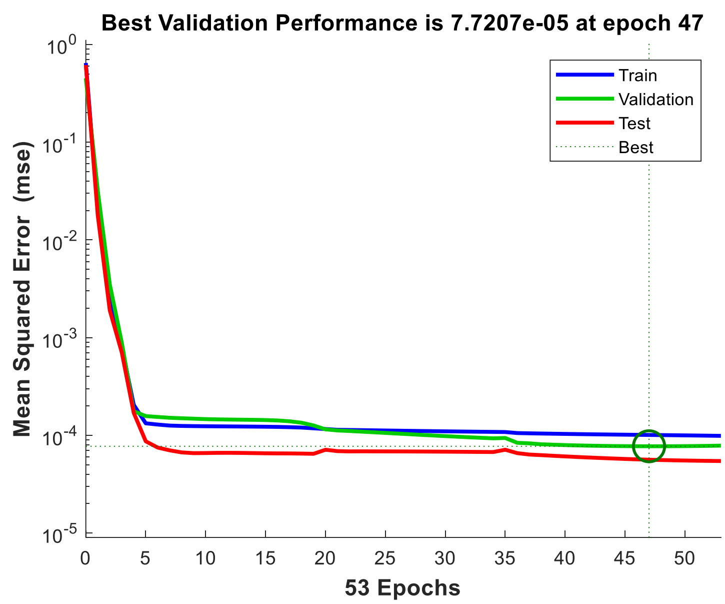

Figure 8. ANN performance for the model between the current and thrust.

According to the figures, the first model takes 13 epochs to reach a normalized RMSE of 1.7×10^{-5} and a regression of 99.993%. The maximum normalized absolute error has an order of 1.5×10^{-2}. On the other hand, the second model between the current and the thrust takes longer time, 46 epochs, to reach a normalized RMSE of 7.7×10^{-5} and a regression of 99.9583%. The maximum normalized absolute error has an order of 2×10^{-2}.

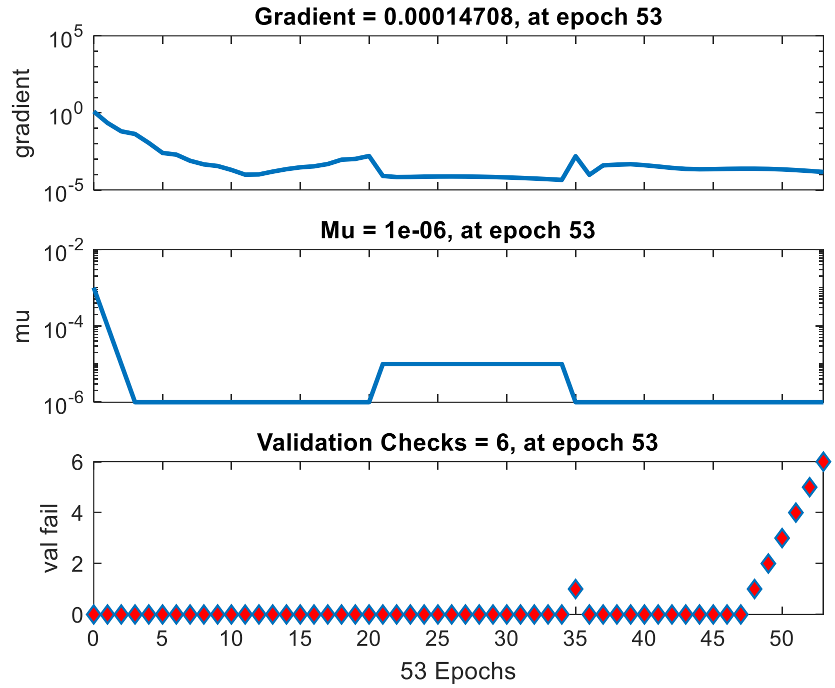

Figure 9. ANN parameters for the model between the current and thrust.

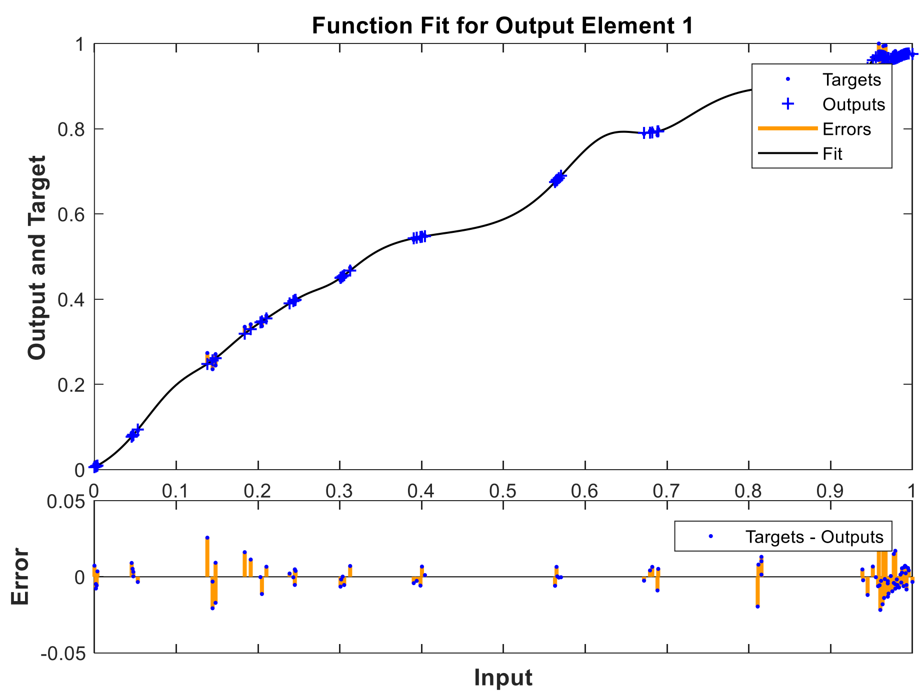

Figure 10. ANN's normalized Output and error for the model between the current and thrust.

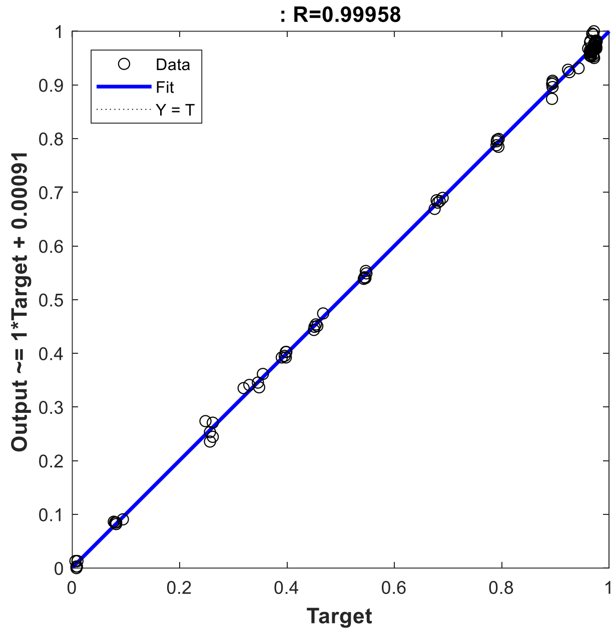

Figure 11. ANN's normalized regression for the model between the current and thrust.

4. CONCLUSION

Two models are developed using artificial neural networks: one finds a relation between the throttle applied to a controller and the current drawn from the batteries, the second finds the relation between the drawn current to thrust obtained from the EDF. Both models have two hidden layers, the first has five and four neurons in its layers, the second one has four and six neurons in its layers. The models have promising results as demonstrated by high regression rates. These models will be studied further, and used in future applications to improve flight performance of UAVs that used electric-powered ducted fans.

ACKNOWLEDGMENT

This research work is sponsored by the University of Sharjah under the grant no. 1602040826-P.

REFERENCES

1- Khaled S Hatamleh, Mohammad Al-Shabi, Adnan Al-Ghasem, and Asad A Asad. "Unmanned aerial vehicles parameter estimation using artificial neural networks and iterative bi-section shooting method." Applied Soft Computing 36, (2015) 457-467.
2- Bryan Kolb and Ian Q Whishaw. "Fundamentals of human neuropsychology." New York: Worth Publishers, 2015. 7th edition. ISBN: 9781429282956.
3- L. Wang and K. Fu. "Artificial neural networks." Wiley Online Library, 2008.
4- R. Hristev. "The ANN Book." Released under the GNU General Public License, 1998.

5- Hugo Alonso, Teresa Mendonça, and Paula Rocha. "Hopfield neural networks for on-line parameter estimation." Neural Networks 22.4 (2009): 450-462.
6- Jun Wu, Makoto Fukuhara, and Tatsuoki Takeda. "Parameter estimation of an ecological system by a neural network with residual minimization training." Ecological modelling 189.3 (2005): 289-304.
7- Minakshi Sharma, and Sourabh Mukharjee. "Brain tumor segmentation using genetic algorithm and artificial neural network fuzzy inference system (ANFIS)." Advances in Computing and Information Technology. Springer Berlin Heidelberg, 2013. 329-339.
8- Tadashi Kondo, Junji Ueno, and Shoichiro Takao. "Medical image diagnosis of liver cancer by feedback GMDH-type neural network using knowledge base." Artificial Life and Robotics 17.3-4 (2013): 488-494.
9- Feng Yin Su, et al. "Research on Hospital Medical Expense Based on BP Neural Network." Proceedings of the International Conference on Information Engineering and Applications (IEA) 2012. Springer London, 2013.
10- Tadashi Kondo, Junji Ueno, and Shoichiro Takao. "Medical image diagnosis of lung cancer by multi-layered GMDH-type neural network self-selecting functions." Artificial Life and Robotics 18.1-2 (2013): 20-26.
11- Ashraf Qadir, William Semke, and Jeremiah Neubert. "Vision Based Neuro-Fuzzy Controller for a Two Axes Gimbal System with Small UAV." (2013).
12- Nan Wang, et al. "A hybrid neural network method for UAV attack route integrated planning." Advances in Neural Networks–ISNN 2009. Springer Berlin Heidelberg, 2009. 226-235.
13- Ioannis K. Nikolos, Eleftherios S. Zografos, and Athina N. Brintaki. "UAV path planning using evolutionary algorithms." Innovations in Intelligent Machines-1. Springer Berlin Heidelberg, 2007. 77-111.
14- Vishwas Puttige, Sreenatha Anavatti, and Tapabrata Ray. "Comparative analysis of multiple neural networks for online identification of a UAV." AI 2007: Advances in Artificial Intelligence. Springer Berlin Heidelberg, 2007. 120-129.
15- Zhengrong Li, et al. "Towards automatic power line detection for a UAV surveillance system using pulse coupled neural filter and an improved Hough transform." Machine Vision and Applications 21.5 (2010): 677-686.
16- Farrukh Mazhar, et al. "On using neural networks in UAV structural design for CFD data fitting and classification." Aerospace Science and Technology 30.1 (2013): 210-225.
17- Juntong Qi, et al. "An adaptive threshold neural-network scheme for rotorcraft UAV sensor failure diagnosis." Advances in Neural Networks–ISNN 2007. Springer Berlin Heidelberg, 2007, 589-596.
18- S. Bonadies, and S. A. Gadsden "An overview of autonomous crop row navigation strategies for unmanned ground vehicles." Engineering in Agriculture, Environment and Food (2019), 12 (1), 24-31
19- S. A. Wilkerson, A. D. Gadsden, and S. A. Gadsden, "An unmanned aerial system for the detection of crops with undergraduate project-based learning." Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping III (2018). International Society for Optics and Photonics (SPIE).
20- O. J Ohanian, III. "Ducted Fan Aerodynamics and Modeling, with Applications of Steady and Synthetic Jet Flow Control." (2011). Dissertation: Virginia Polytechnic Institute.
21- J. Fehrenbacher, "Electric Motor & Power Source Selection for Small Aircraft Propulsion." 2011. Purdue University.
22- J.M. Budinger, S.D. Kerslake, L.A. Nagy, M.J. Shalkhauser, N.J. Soni M.A. Cauley, J.H. Mohamed, J.B. Stover, R.R. Romanofsky, P.J. Lizanich, and D.J. Mortensen. "Quaternary Pulse Position Modulation Electronics for Free-Space Laser Communications." Conference on Advanced Space Exploration Initiative Technologies, cosponsored by the AIAA, NASA, and OAI, Cleveland, Ohio, September 4-6, 1991.
23- https://www.turbines-rc.com/en/jp-hobby/1622-edf-ducted-fan-jp-hobby-120mm-12s-motor-760kv-cw.html
24- M. Gerber. "Motor, Propeller, ESC, and Battery Sizing Introduction." (2016). http://www.maclab.seas.ucla.edu/people/matt-gerber/
25- https://www.turbines-rc.com/en/50a-and-over/1291-jp-hobby-mantis-150a-hv-esc-6-12s-opto.html

26- Arne Niitsoo, Thorsten Edelhaußer, and Christopher Mutschler. “Convolutional Neural Networks for Position Estimation in TDoA-based Locating Systems.” 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 24-27 September 2018, Nantes, France.

27- Simon Pfreundschuh, Patrick Eriksson, David Duncan, Bengt Rydberg, Nina Håkansson, and Anke Thoss. “A neural network approach to estimating a posteriori distributions of Bayesian retrieval problems.” Atmos. Meas. Tech., 11, (2018), 4627–4643.

28- Yusuke Manabe, and Basabi Chakraborty. "A novel approach for estimation of optimal embedding parameters of nonlinear time series by structural learning of neural network." Neurocomputing 70.7 (2007): 1360-1371.

29- K. Chang, P. Rammos, S. A. Wilkerson, M. Bundy, and S. Andrew Gadsden "LiPo battery energy studies for improved flight performance of unmanned aerial systems", Proc. SPIE 9837, Unmanned Systems Technology XVIII, 98370W (13 May 2016).

30- Andrew Lee, Ed Habtour, and S. Andrew Gadsden, "Proposed health state awareness of helicopter blades using an artificial neural network strategy", Proc. SPIE 9872, Multisensor, Multisource Information Fusion: Architectures, Algorithms, and Applications 2016, 98720C (19 May 2016).

31- S. A. Gadsden, M. Al-Shabi, and S. R. Habibi. “Estimation strategies for the condition monitoring of a battery system in a hybrid electric vehicle.” ISRN Signal Processing 2011.

32- Richard Bustos, Abu Raihan Mohammad Siddique, Taranjit Cheema, S. Andrew Gadsden, and Shohel Mahmud. “State Of Charge And Parameter Estimation Of Electric Vehicle Batteries.” Proceedings of The Canadian Society for Mechanical Engineering International Congress 2018. CSME International Congress 2018, May 27-30, 2018, Toronto, On, Canada.