Preliminary study of actuator fault detection for RUAVs using neuro-fuzzy system

T., Thanaraj; Ng, Bing Feng; Low, Kin Huat

2021

T., T., Ng, B. F. & Low, K. H. (2021). Preliminary study of actuator fault detection for RUAVs using neuro-fuzzy system. AIAA SciTech 2021 Forum, 1-9.
<https://dx.doi.org/10.2514/6.2021-1055>

<https://hdl.handle.net/10356/147380>

<https://doi.org/10.2514/6.2021-1055>

© 2021 Nanyang Technological University. Published by the American Institute of Aeronautics and Astronautics, Inc., with permission.

Downloaded on 26 Apr 2023 23:31:43 SGT

Preliminary Study of Actuator Fault Detection for RUAVs using Neuro-Fuzzy System

Thanaraj T.¹, Bing Feng Ng², Kin Huat Low³

¹*Air Traffic Management Research Institute*

^{2,3}*School of Mechanical and Aerospace Engineering
Nanyang Technological University, Singapore 639798*

With the ever-increasing use of Rotary Unmanned Aerial Vehicles (RUAVs) for various purposes, a fast and accurate fault detection system is key to detect unknown faults, to ensure fault tolerance and for safe operations. In this paper, a data-driven fault detection algorithm based on an Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to detect single actuator faults of quadrotor flights through sensor readings from inertial measurement units. Sensor readings were collated and pre-processed to generate a training dataset to train the neuro-fuzzy model, and then the trained model was evaluated using four-fold cross-validation and a set of performance metrics. The results presented illustrate the generalisation performance ANFIS model and its effectiveness in detecting actuator faults.

I. Introduction

In recent years, there had been an increase in the use of Rotary Unmanned Aerial Vehicles (RUAVs) given their capabilities in lateral maneuver, hover, vertical take-off, and landing. As a result, RUAVs are favoured over fixed-wing UAVs to take on missions such as low altitude aerial photography, cargo delivery, humanitarian, search-and-rescue operations, etc. To be highly agile and undertake challenges in these complex missions, RUAVs have sophisticated automatic control systems where they can control the position and attitude by varying the velocities of the propellers and motors. However, these components are prone to damage or degradation over time, leading to actuator faults. These faults can result in poor performance and instability of the RUAV's control system, and eventually, compromise on safety and potentially lead to fatal crashes [1], property damages or even, collisions with other aircraft [2]. Hence, it is imperative that a fault detection system is incorporated into the RUAV's control system that is capable to detect fault occurrences accurately and precisely.

There are a variety of existing studies that carried out fault detection on RUAVs, which can be generally categorized as model-based or data-driven approaches. Model-based fault detection involves generating mathematical models analytically to describe the nonlinear dynamics of the aircraft of interest. They employ observers or estimators to generate residuals, which are key to fault detection and diagnosis. Unknown input observers [3,4], sliding mode observers [5] and Thau observers [6–8] are a few examples of observer-based fault detection carried out for actuator and sensor faults. Furthermore, model-based fault detection designs also employ estimators, such as Kalman filters, that are usually used in stochastic systems to estimate states and parameters of a system. There are several variations of Kalman filters used in the literature for detecting and diagnosing actuator and sensor faults, such as traditional Kalman Filter [9], Extended Kalman Filter [10] and Unscented Kalman Filter [11,12], where each variation caters to a different degree of nonlinearity present in the fault detection problem. Despite exhibiting good performances,

¹ PhD Student, Air Traffic Management Research Institute (contact: tthanara001@e.ntu.edu.sg_

² Assistant Professor, School of Mechanical and Aerospace Engineering (contact: bingfeng@ntu.edu.sg)

³ Professor, School of Mechanical and Aerospace Engineering (contact: mkhlow@ntu.edu.sg)

observers and estimators fundamentally adopt mathematical models for their designs, which can inevitably cause an increase in complexity when greater nonlinearity is considered.

In contrast, data-driven fault detection techniques are favoured over model-based ones as they require a large amount of observational data to perform and thus, reducing the dependability on complex mathematical models. These approaches employ knowledge-based or machine learning techniques and have been used to detect faults on UAVs. In one study, actuator faults on a quadrotor were detected using Artificial Neural Network (ANN) [13] while in another, deep neural networks were used to detect both actuator and sensor faults with the aid of color image obtained from time-frequency-amplitude graphs [14]. Furthermore, support vector machines classification method was used to detect actuator faults offline on a fixed-wing UAV [15] whereas in another study neural networks were augmented with an Extended Kalman Filter, for weight updating, to detect both actuator and sensor faults online [16]. Data-driven techniques face their challenges as well, where they are required to handle large amounts of data that can have numerous dimensions, thus, suffering from the curse of dimensionality. Neuro-fuzzy systems, on the other hand, combines the robust learning capabilities of ANN and the enhanced reasoning and inference capabilities of Fuzzy Logic systems, resulting in the system being capable of dealing with cognitive uncertainties. One commonly used neuro-fuzzy system is ANFIS [17], which had been used in fault detection designs for industrial applications, such as for wind turbine pitch faults [18] and faults in steam turbine [19], rotating machinery [20] and in detecting navigational sensor faults in UAVs [21].

This paper focuses on studying the performance of an actuator fault detection algorithm that employs a neuro-fuzzy system for an UAV in hovering condition. The overall fault detection model is designed with the UAV's control system and ANFIS. Following which, flight simulations were carried out for a quadrotor UAV to generate data from an inertial measurement unit (IMU) sensor, which was then used as feature vectors to train and test the data-driven fault detection model. The performance of the trained model is evaluated with a set of performance metrics and then applied to a new set of faults.

II. Data-driven Fault Detection Model

Given that UAVs are highly nonlinear systems, it is crucial that the data-driven model captures the important features from the UAV's system and control model and provide good generalization performances. The overview of the fault detection model is illustrated in Figure 1. A system and control model of the UAV of interest was created in MATLAB SIMULINK software to generate IMU sensor data, which was then pre-processed and used to create an offline training dataset with normal and faulty actuator data. Next, fuzzy rules were extracted from this dataset for neuro-fuzzy rule training. The trained ANFIS model was tested on testing data, from which the trained model's performance in fault classification was analyzed.

Figure 1: Framework of fault detection model

A. RUAV System and Control Model

The general architecture of the RUAV's closed-loop system and control model is presented in Figure 2 with four major segments: controller, actuators, RUAV dynamical model, and sensors. In the controller segment, two sets of PID controllers use residuals from input command and state feedback to stabilize the RUAV's position and attitude. A set of nonlinear equation with six degrees-of-freedom over the earth fixed frame was modelled into the RUAV dynamical model. Faults were injected into the actuator segment to simulate actuator faults whereas the resulting IMU sensor data was collected for normal and faulty flight conditions and subsequently used for the fault detection algorithm.

Figure 2: RUAV System and Control Model

B. Fault Design

In the fault detection model, actuator faults were considered as partial loss of effectiveness in the actuator. For example, degradation or damage to the actuator would cause a reduction in thrust provided by an actuator. The actuator faults were modelled as multiplicative fault, given by:

$$\Omega'_i = \gamma \Omega_i \quad (1)$$

where Ω'_i is the actual angular velocity of the rotor, Ω_i is the commanded angular velocity for the i^{th} rotor, where $i = 1, \dots, m$, with m being the number of rotors fitted on the RUAV. In the case of a faultless actuator, $\gamma = 1$, while for the case of faulty actuator with partial loss of effectiveness, $\gamma < 1$, where a lower bound was determined through simulations to ensure stable recovery of the RUAV from the fault.

C. ANFIS Model

Adaptive Neuro-Fuzzy Inference System was originally proposed by Jang [17] which combines Artificial Neural Network (ANN) and fuzzy logic systems. A typical ANFIS architecture is similar to a first-order Takagi-Sugeno fuzzy system, where two inputs x_1 and x_2 , and one output y are considered, as shown in Figure 3. Here, with the use of a first-order Sugeno fuzzy, a set of common fuzzy if-then rules are generated and modelled into the crisp outputs. A set of fuzzy if-then rules for the given ANFIS architecture is as follows:

$$\left(\begin{array}{l} \text{if } x_1 \text{ is } A_{11}, x_2 \text{ is } A_{21}, \text{ then } f_1 = p_1 x_1 + q_1 x_2 + r_1 \\ \text{if } x_1 \text{ is } A_{11}, x_2 \text{ is } A_{22}, \text{ then } f_2 = p_2 x_1 + q_2 x_2 + r_2 \\ \text{if } x_1 \text{ is } A_{12}, x_2 \text{ is } A_{21}, \text{ then } f_3 = p_3 x_1 + q_3 x_2 + r_3 \\ \text{if } x_1 \text{ is } A_{13}, x_2 \text{ is } A_{22}, \text{ then } f_4 = p_4 x_1 + q_4 x_2 + r_4 \end{array} \right) \quad (2)$$

where x_i represents the input for $i = 1, 2 \dots n$ with n being the total number of inputs, A_{ij} refers to the associated linguistic label for $j = 1, 2 \dots N$ with N being total number of membership functions per input. On the other hand, $\{p_k, q_k, r_k\}$ refer to the consequent parameter set for the k^{th} rule, which will be updated during training. The ANFIS architecture in Figure 3 has a combination of square nodes and circle nodes. The square nodes in Layer 1 and Layer 4 are adaptive nodes, whose parameters are tuned during the training phase whereas the circle nodes are fixed nodes. Nodes in the same layer perform similar functions and are described as follows:

Figure 3: ANFIS architecture for two inputs and nine rules

Layer 1: Fuzzification Layer: In this layer, each input is associated with its linguistic variables based on a set of defined membership functions. Each fuzzification node in this layer is adaptive and generates an output, given as:

$$Out_{i,j}^{(1)} = \mu_{A_j}(x_i) \quad (3)$$

where the output represents the membership grade of the input x_i to the fuzzy membership functions, and A_j refers to the linguistic fuzzy labels. Any appropriate parameterized function can be used to model the membership functions, but it is recommended to use differentiable functions, such as the generalized bell function, defined as:

$$\mu = \frac{1}{1 + \left| \frac{x_i - c_j}{a_j} \right|^{2b_j}} \quad (4)$$

where, $\{a_j, b_j, c_j\}$ are premise parameters tuned during the training phase.

Layer 2: Product Layer: This layer contains the rules that generate firing strength. Usually, for an ANFIS model that uses grid-partitioning, there will be N^n nodes generated in this layer where each of them produces the product of the incoming signals as follows:

$$Out_k^{(2)} = w_k = \mu_{A_j}(x_1) \times \mu_{A_j}(x_2), \quad j = 1, 2; \quad k = 1, 2, 3, 4 \quad (5)$$

Layer 3: Normalisation Layer: The nodes in this layer generates the normalized firing strength, by taking its corresponding firing strength's ratio with respect to the sum of all firing strengths, defined as:

$$Out_k^{(3)} = \bar{w}_k = \frac{w_k}{\sum_k w_k}, \quad k = 1, 2, 3, 4 \quad (6)$$

Layer 4: Defuzzification Layer: The nodes in this layer are adaptive nodes, which produce crisp outputs that are a product of the incoming normalized firing strengths and a first-order polynomial function defined by the consequent parameter set, given as:

$$Out_k^{(4)} = \bar{w}_k f_k = w_k (p_k x_1 + q_k x_2 + r_k), \quad k = 1, 2, 3, 4 \quad (7)$$

Layer 5: Summation Layer: This layer contains only one fixed node that sums all the crisp outputs from the previous layer as such:

$$Out_k^{(5)} = y = \sum_k \bar{w}_k f_k, \quad k = 1, 2, 3, 4 \quad (8)$$

The layers presented above define the structure of ANFIS as shown in Figure 3, where $Out^{(L)}$ represents the output of the L^{th} layer. To train the premise and consequent parameters, a hybrid learning algorithm is adopted that consists of two passes in one training epoch, forward and backward pass. Firstly, in the forward pass, the premise parameters are kept constant while the consequent parameters are tuned using the least squares method. Once an optimum set of consequent parameters is reached, the backward pass initiates with the consequent parameter set kept constant and the premise parameters tuned using the gradient descent method. This forward and backward process repeats until the training reaches a user-defined number of maximum epochs or the overall root mean squared error between target and actual output reaches a specified value. The gradient descent method is a computationally intensive method and seen from Layer 2, the number of rules increases exponentially with the number of inputs, and as a result, computational complexity increases. As such, it is generally recommended to limit the number of inputs to only those that present significant features sufficient to train the ANFIS model.

III. Simulation and Results

In this section, performance of the data-driven fault detection system using ANFIS in classifying actuator fault on a quadrotor UAV was analyzed. The flight simulations, offline training and testing of the ANFIS-based fault detection model were carried out on MATLAB/SIMULINK r2020a software with computation done in an Intel(R) Core (TM) i7-10750H CPU @ 2.60GHz. The data collected from a noisy IMU sensor has six sets of readings: accelerometer readings in x, y, z-directions given by $\{\ddot{x}, \ddot{y}, \ddot{z}\}_{acc}$, and gyroscope readings about the x, y, z-axes given by $\{\dot{p}, \dot{q}, \dot{r}\}_{gyro}$. To generate the readings, an actuator fault was injected, and the corresponding accelerometer and gyroscope readings were analyzed. Subsequently, only three of the readings were selected as they exhibited unique features when single actuator faults were injected for each of the four actuators. Figure 4 shows the six readings for faulty conditions. When one actuator experiences 5% loss of effectiveness momentarily, $\gamma = 0.95$, and it can be seen that accelerometer readings in x, y-directions, $\{\ddot{x}, \ddot{y}\}_{acc}$, and gyroscope readings about z-axis, $\dot{r}_{gyro}$, show more distinctive readings in a noisy environment as compared to the other three.

A preliminary study was carried out to determine the optimum number of membership functions per input required to achieve the best generalization performance for a trained ANFIS model. In this study, five different flight simulations were conducted with one under normal condition, and four under faulty conditions, where a single actuator fault was applied to each of the four actuators on a quadrotor UAV, at a sampling rate of five samples per second. 200 data pairs of IMU readings were collected from the flight simulations under normal condition. The remaining of the four flight simulations under faulty conditions corresponded to each of the four actuators on the quadrotor UAV injected with eight separate five seconds actuator fault. Following this, the corresponding IMU readings during the fault occurrence were collected. Each fault occurrence produced 25 data pairs and hence, with eight separate faults induced for each of the four actuators on the UAV, 800 data pairs of IMU readings were collected. Here input-output data pair contained three IMU readings and the corresponding Boolean fault classification (1 representing faulty flight condition and 0 representing normal flight conditions). The collected data pairs were made up to a training dataset that contained 1000 input-output data pairs which were then split, where 75% of the data was used to train the ANFIS model, while the remaining 25% was used for validating the trained model for an unbiased evaluation. Next, confusion matrix analysis was conducted to study the performance of the ANFIS model as a fault classifier [22], and a set of performance metrics were used to further analyze the classification, namely, accuracy, precision, recall and F1 score. The two-by-two confusion matrix for fault detection is given in Table 1 and the associated performance metrics are given in Equations 9 to 12.

Here, true positive refers to the number of instances for which the model detects fault when there is an actual fault while true negative represents the number of instances at which no fault was predicted in the event of normal condition. False positive refers to the model incorrectly predicting the presence of a fault while false negative refers to a missed detection where the trained model incorrectly predicts that there is no fault. As for the performance metrics, each of

them ranges from 0 to 1, where a higher number represents a better performance by the trained model in detecting faults. Firstly, accuracy refers to the number of instances the predictions by the trained model is correct as a ratio to the total number of predictions. Next, precision represents the number of instances the model correctly predicts a fault divided by the number of times the model predicts fault, while recall, also referred to as true positive rate, refers to the number of instances the model correctly predicts a fault divided by the number of instances at which there was an actual fault. Lastly, F1 score acts as a harmonic mean between precision and recall to represents the test's accuracy and this measure is favored when there is an uneven class of distribution by establishing a balance between precision and recall.

Figure 4: Accelerometer and gyroscope readings extracted from IMU for one actuator fault condition

Table 1: Confusion Matrix Analysis for Fault Detection

		Actual	
		Fault	No Fault
Predicted	Fault	<i>True Positive</i>	<i>False Positive</i>
	No Fault	<i>False Negative</i>	<i>True Negative</i>

$$Accuracy = \frac{TP + FN}{TP + FP + FN + TN} \quad (9)$$

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

$$Precision = \frac{TP}{TP + FP} \quad (11)$$

$$F1\ Score = 2 \times \frac{precision \times recall}{precision + recall} \quad (12)$$

Using four-fold cross-validation, the training dataset was divided into four equal sections A, B, C and D, where each section was used as testing dataset for four different pieces of trainings, as shown in Table 1. This was a measure to ensure the trained model was not overfitting and hence, provided good generalization performances. The ANFIS model was trained with generalized bell functions as membership functions and the trained model tested for a varying number of membership functions per input in each train-test split. Following which, the resulting confusion matrices were collected and used to evaluate the performance metrics. The performance metrics for train-test split 1 are shown in Table 2 while Table 3 presents the corresponding confusion matrices for a varying number of membership functions.

Table 2: Train-test splits for four-fold cross validation

Train-Test Split	Sections used for:	
	Training	Testing
1	A, B, C	D
2	A, B, D	C
3	A, C, D	B
4	B, C, D	A

Table 3: Performance metrics for train-test split 1 (ABC-D)

No. of membership functions per input	Accuracy	Recall	Precision	F1 Score
2	0.8520	0.9854	0.8565	0.9164
3	0.8800	0.8932	0.9583	0.9246
4	0.8880	0.9029	0.9587	0.9300
5	0.8720	0.8883	0.9531	0.9195
6	0.8320	0.8252	0.9659	0.8900
7	0.8480	0.8495	0.9615	0.9020

Table 4: Confusion matrices for train-test split 1 (ABC-D)

		Actual											
		Number of membership functions											
		2		3		4		5		6		7	
		F	NF	F	NF	F	NF	F	NF	F	NF	F	NF
Predicted	F	203	34	184	8	186	8	183	9	170	6	175	7
	NF	3	10	22	36	20	36	23	35	36	38	31	37

Following the cross-validation, the accuracy and F1 score of the ANFIS model's fault classification were compared with varying number of membership functions. Generally, the classification performance should increase as the number of membership function was increased. However, as shown in Figure 5, the accuracy and F1 score metric reduced after a certain number of membership functions, suggesting that the model started to experience overfitting. Also, both plots in Figure 5 show that the optimum number of membership functions to be used to achieve the best performance was four, resulting in an average accuracy and F1 score of 0.8840 and 0.9254, respectively, as highlighted in Table 5.

Table 5: Average values of the performance metrics for four train-test splits

No. of membership functions per input	Accuracy	Recall	Precision	F1 Score
2	0.8200	0.9914	0.8220	0.8981
3	0.8800	0.9121	0.9376	0.9241
4	0.8840	0.8992	0.9537	0.9254
5	0.8760	0.8868	0.9557	0.9197
6	0.8520	0.8573	0.9543	0.9027
7	0.8490	0.8517	0.9551	0.9003

Figure 5: Performance of ANFIS with varying number of membership functions (a) Accuracy (b) F1 Score

IV. Concluding Remarks

The performance of ANFIS used in a data-driven fault detection algorithm to detect RUAV actuator faults has been presented in this paper. Simulation flights were conducted using a quadrotor RUAV model in MATLAB/SIMULINK software, following which, IMU sensor readings were collected for normal (faultless) flight conditions and faulty (single actuator fault) flight conditions. The data collected was consolidated and pre-processed to generate a training dataset for ANFIS model training and then, four-fold cross validation was conducted by splitting the training dataset into four equal sections. Besides, confusion matrices were generated for each train-test split and were used to analyse the performance of ANFIS for varying number of membership functions per input, based on a set of performance metrics: accuracy, precision, recall and F1 score. The results show that the trained ANFIS model produced the best generalization performance, in terms of accuracy and F1 score, when four membership functions per input were used and, greater number of membership functions do not necessarily increase the performance of the trained model. However, it should be noted that the results of the performance metrics presented are unique to the training dataset used in this study. Also, the trained model is limited in its performance as exogenous disturbances, such as wind, usually present during actual flights, were not considered in the simulated flights. In future works, a larger dataset will be used to train the ANFIS model to improve the reliability of the fault detection algorithm. Also, this algorithm will be improved to enable it to isolate and estimate the severity of actuator faults.

Acknowledgement

This research is supported by the Civil Aviation Authority of Singapore and Nanyang Technological University, Singapore under their collaboration in the Air Traffic Management Research Institute. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of the Civil Aviation Authority of Singapore. The PhD candidature scholarship provided to the first author by Nanyang Technological University through Air Traffic Management Research Institute Leader's Track is greatly appreciated.

References

- [1] Koh, C. H., Deng, C., Li, L., Zhao, Y., Tan, S. K., Chen, Y., Yeap, B. C., Li, X., and Low, K. H., "Experimental and Simulation Weight Threshold Study for Safe Drone Operations," *2018 AIAA Information Systems-AIAA Infotech @ Aerospace*, No. 2018-1725, Kissimmee, Florida, 2018.
- [2] Liu, H., Mohd, H. C. M., Ng, B. F., and Low, K. H., "Airborne Collision Evaluation between Drone and Aircraft Engine: Effects of Position and Posture on Damage of Fan Blades," *AIAA AVIATION 2020 FORUM*, American Institute of Aeronautics and Astronautics.
- [3] Avram, R. C., Zhang, X., Campbell, J., and Muse, J., "IMU Sensor Fault Diagnosis and Estimation for Quadrotor UAVs," *9th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes SAFE PROCESS*, No. 48, Paris, France, 2015.
- [4] Avram, R. C., Zhang, X., and Muse, J., "Quadrotor Sensor Fault Diagnosis with Experimental Results," *Journal of Intelligent & Robotic Systems*, Vol. 86, No. 1, 2017, pp. 115–137. <https://doi.org/10.1007/s10846-016-0425-1>.
- [5] Saied, M., Shraim, H., Francis, C., Fantoni, I., and Lussier, B., "Actuator Fault Diagnosis in an Octorotor UAV Using Sliding Modes Technique: Theory and Experimentation," *2015 European Control Conference (ECC)*, Linz, Austria, 2015.
- [6] Freddi, A., Longhi, S., and Monteriù, A., "A Diagnostic Thau Observer for a Class of Unmanned Vehicles," *Journal of Intelligent & Robotic Systems*, Vol. 67, No. 1, 2012, pp. 61–73. <https://doi.org/10.1007/s10846-012-9650-4>.
- [7] Cen, Z., Noura, H., Susilo, T. B., and Younes, Y. A., "Robust Fault Diagnosis for Quadrotor UAVs Using Adaptive Thau Observer," *Journal of Intelligent & Robotic Systems*, Vol. 73, No. 1, 2014, pp. 573–588. <https://doi.org/10.1007/s10846-013-9921-8>.
- [8] Nguyen, N. P., and Hong, S. K., "Sliding Mode Thau Observer for Actuator Fault Diagnosis of Quadcopter UAVs," *Applied Sciences*, Vol. 8, No. 10, 2018, p. 1893. <https://doi.org/10.3390/app8101893>.
- [9] Lyu, P., Liu, S., Lai, J., and Liu, J., "An Analytical Fault Diagnosis Method for Yaw Estimation of Quadrotors," *Control Engineering Practice*, Vol. 86, 2019, pp. 118–128. <https://doi.org/10.1016/j.conengprac.2019.03.010>.
- [10] Zhong, Y., Zhang, W., and Zhang, Y., "Sensor Fault Diagnosis for Unmanned Quadrotor Helicopter via Adaptive Two-Stage Extended Kalman Filter," *International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC)*, Shanghai, China, 2017.
- [11] Qi, J., Song, D., Wu, C., Han, J., and Wang, T., "KF-Based Adaptive UKF Algorithm and Its Application for Rotorcraft UAV Actuator Failure Estimation," *International Journal of Advanced Robotic Systems*, Vol. 9, No. 4, 2012, p. 132. <https://doi.org/10.5772/51893>.
- [12] Lu, P., Eykeren, L. V., Kampen, E.-J. van, and Chu, Q. P., "Sensor Fault Detection and Estimation for Quadrotors Using Kinematic Equations," *Advances in Aerospace Guidance, Navigation and Control*, 2015, pp. 363–379. https://doi.org/10.1007/978-3-319-17518-8_21.
- [13] Jiang, Y., Zhiyao, Z., Haoxiang, L., and Quan, Q., "Fault Detection and Identification for Quadrotor Based on Airframe Vibration Signals: A Data-Driven Method," *34th Chinese Control Conference (CCC)*, Hangzhou, China, 2015.
- [14] Olyaei, M. H., Jalali, H., Noori, A., and Eghbal, N., "Fault Detection and Identification on UAV System with CITFA Algorithm Based on Deep Learning," *26th Iranian Conference on Electrical Engineering (ICEE)*, Mashhad, Iran, 2018.
- [15] Baskaya, E., Bronz, M., and Delahaye, D., "Fault Detection Diagnosis for Small UAVs via Machine Learning," *IEEE/AIAA 36th Digital Avionics Systems Conference (DASC)*, St. Petersburg, Florida, USA, 2017.
- [16] Abbaspour, A., Aboutalebi, P., Yen, K. K., and Sargolzaei, A., "Neural Adaptive Observer-Based Sensor and Actuator Fault Detection in Nonlinear Systems: Application in UAV," *ISA Transactions*, Vol. 67, 2017, pp. 317–329. <https://doi.org/10.1016/j.isatra.2016.11.005>.
- [17] Jang, J.-R., "ANFIS: Adaptive-Network-Based Fuzzy Inference System," *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 23, No. 3, 1993, pp. 665–685. <https://doi.org/10.1109/21.256541>.
- [18] Chen, B., Matthews, P. C., and Tavner, P. J., "Wind Turbine Pitch Faults Prognosis Using A-Priori Knowledge-Based ANFIS," *Expert Systems with Applications*, Vol. 40, No. 17, 2013, pp. 6863–6876. <https://doi.org/10.1016/j.eswa.2013.06.018>.
- [19] Salahshoor, K., Kordestani, M., and Khoshro, M. S., "Fault Detection and Diagnosis of an Industrial Steam Turbine Using Fusion of SVM (Support Vector Machine) and ANFIS (Adaptive Neuro-Fuzzy Inference System) Classifiers," *Energy*, Vol. 35, No. 12, 2010, pp. 5472–5482. <https://doi.org/10.1016/j.energy.2010.06.001>.
- [20] Lei, Y., He, Z., Zi, Y., and Hu, Q., "Fault Diagnosis of Rotating Machinery Based on Multiple ANFIS Combination with GAs," *Mechanical Systems and Signal Processing*, Vol. 21, No. 5, 2007, pp. 2280–2294. <https://doi.org/10.1016/j.ymssp.2006.11.003>.
- [21] Sun, R., Cheng, Q., Wang, G., and Ochieng, W. Y., "A Novel Online Data-Driven Algorithm for Detecting UAV Navigation Sensor Faults," *Sensors*, Vol. 17, No. 10, 2017, p. 2243. <https://doi.org/10.3390/s17102243>.
- [22] Fawcett, T., "An Introduction to ROC Analysis," *Pattern Recognition Letters*, Vol. 27, No. 8, 2006, pp. 861–874. <https://doi.org/10.1016/j.patrec.2005.10.010>.