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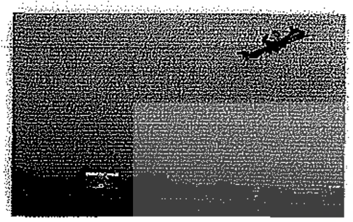

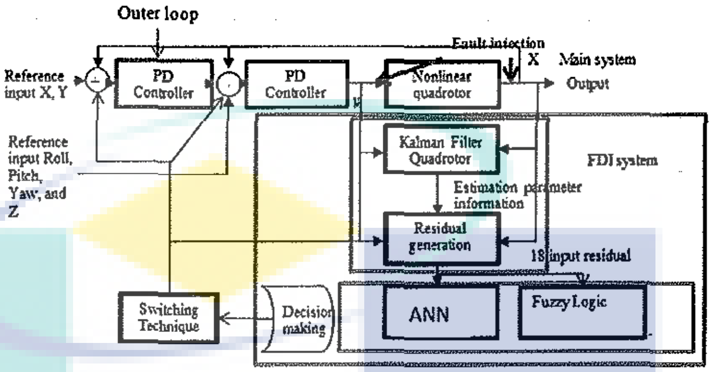

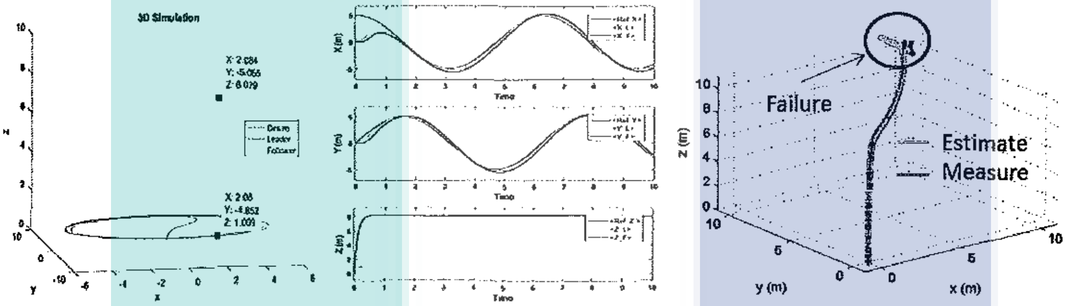

A NEW HYBRID METHOD BASED ON KALMAN FILTER AND ADAPTIVE NEURAL NETWORK FOR THE ROBUSTNESS IMPROVEMENT OF FAULT DETECTION AND IDENTIFICATION PROCESS

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ABSTRACT

This project assesses the possibility of a new hybrid method based on Kalman Filter and Adaptive Neural Network for the robustness improvement of Fault Detection and Identification (FDI) Process. Two classes of approaches are introduced, 1) the system identification approach and 2) the observer-based approach using the Kalman filter. The

Kalman filter recognizes data from the sensors of the system and indicates the fault of the system in the sensor reading. Error prediction is based on the fault magnitude and the time occurrence of fault. A representative Artificial Neural Network (ANN) model is designed and used to classify the fault class. The proposed technique is implemented on a quad-rotor Micro-Aerial Vehicle (MAV) as a complex system that has Multi Input Multi Output (MIMO). In particular, two FDI scenarios are considered: 1) the estimation of an unknown actuator fault and 2) an unknown sensor fault. The result comparison of the residual signal before filter and after filter showed that Kalman-ANN is able to identify and immediately acknowledge the system to operate in the normal state. By comparing the system performance of the FDI technique, Kalman-ANN is more effective in identifying parts of the system that experiences failure. Kalman- ANN is also able to acknowledge user on the parts of quadrotor that experience failure and provide user with the best instructions or solutions for the situation, ensuring a safe landing.

1. INTRODUCTION

In practice, unwanted condition exists in the systems and these are commonly called as faults. Faults usually occurred due to component and interconnection failures, parameter shifting, sudden environmental variations, etc.[1] For a close loop control system, these faults may lead to a poor performance or even instability when they occur in actuators, sensors or controllers. In order to improve the reliability, safety and efficiency of a system especially the performance, fault-detection and fault diagnosis has become increasingly important in many technical processes of the control system. It is crucial to detect and identify the faults and failures as quickly as possible so that appropriate decisions or remedies can be made.[2] Thus, the problem of fault detection in dynamic systems has become a topic for intensive research. Fault detection is especially important in the area of mini transportation, reliability and safety of aerial vehicles due to a growing demand of reliability and safety for aerial vehicles.[3]

Fault detection system and fault tolerant control system were developed to over-come these challenges such as health monitoring, early warning, fault detection, automated fault tolerant control, and recovery of upset or loss of control.[4][5] Fault detection (FD) system is coupled with the engineering application of automatic control system to identify the type of fault and its location. The concept of automatic FD is used to critically address this type of problems and a number of promising results have been reported.[6][7] FD system provides formula to identify the fault that exists in the control system. Various studies have been conducted to perform FDI task, where the three types of function are[8]:

- Fault detection: to detect when something wrong with the system
- Fault isolation: to reduce the potential damage and make the system easy to maintain
- Fault identification: to estimate the type of the fault, fault magnitude and nature of the fault.

Fault detection and identification methods can be classified by the way process knowledge is incorporated in the signal processing, into Mathematical based methods and intelligent based methods. When a process is too complex to be modelled analytically a fault detection approach based on complex systems signal analysis doesn't yield an unambiguous diagnosis.
In order to visualise the impacts, the unmanned system named Micro aerial vehicle (MAV) is selected for research purposes. MAV is a class of miniature Unmanned Aerial

Vehicle system (UAV) that has a size restriction. Modern MAV can be as small as 15 centimetres. Development is driven by commercial, research, government, and military purposes; with insect-sized aircraft reportedly expected in the future. MAV or flying robot have also attracted enormous interest among researchers in the past and are widely used as valuable tools in today's society.[9]

MAV offers several advantages over the manned systems due to its low cost, low radar signatures and less risk to crews. Vertical take-off and landing type MAV exhibits further advantages in manoeuvrability features.[10] One of the famous types of mini-aerial vehicle that offers great potential is the four-rotor aerial vehicle, namely quadrotor. Quadrotor is a multirotor helicopter which consists of four rotors/propellers that can lift the body up to the air. It is a flying vehicle (transportation) which is used in rapidly spinning rotors to push air upwards to create a trust force that keeps the quadrotor fix in its location in space. Consisting of four independent rotors, this mechanism allows the quadrotor to utilize more degree of freedom with the same level of control as compared to the two rotors helicopter.

Quadrotor has great potential in many areas. The strength of quadrotor is that it can reach dangerous place or area that is unreachable by human. It also allows people to experience the flying game, dive into smaller hole and at the same time sending information or high-altitude video camera.

It is therefore crucial to ensure that quadrotor system can work properly and efficiently. The implementation of quadrotor system must consider possible system failures, diagnoses and emergency safety landing procedure so that when quadrotor performing its task, errors and losses can be minimized. In achieving this objective, fault detection system and fault tolerant control system were developed.

Several researches have been conducted on FDI system using different techniques in quadrotor system. However they can only detect the sensor and actuator faults. These techniques cannot detect extra advent on the lift fault that exist inside the quadrotor, as it was thought to be fixed by the proportional–integral–derivative controller (PID controller), Fuzzy controller and other components, which in reality, was not resolved. The lift fault may be due to various issues including the connection loss between the wing and the rotor, broken propeller, the irregular size of the wing and other failure. Inability to detect lift fault of the rotor will pose severe impacts to the entire fly system.

2. RESEARCH METHODOLOGY

This project is divided into several tasks:

1) Choose a complex system to be used as the platform in the project. In this case, quad-rotor Micro Aerial Vehicle (MAV) is used,
2) Mathematical modelling of the system,
3) Controller design of the system,
4) Design of Bank of Kalman filter for residual generator,
5) Neural network design, and
6) Validation of the proposed method.

2.1 Complex system : Quad-rotor MAV

Quad-rotor Micro Aerial Vehicle (MAV) is used as the representation of complex system. The physical of MAV is shown in Figure 1.

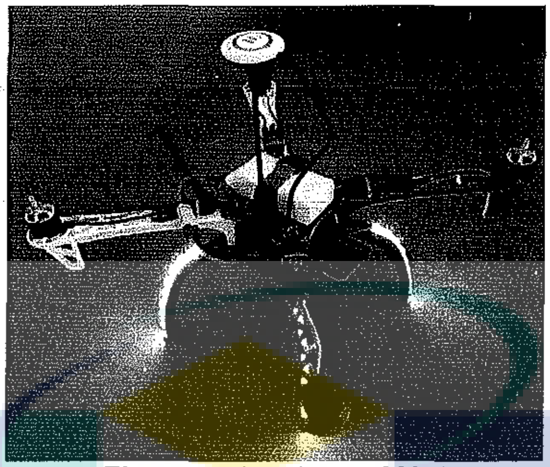

Figure 1: Quad-rotor MAV

Quad-rotor consists of two pairs of identical fixed pitched propellers; two clockwise (CW) and two counterclockwise (CCW). Four propellers use independent speed variation of each rotor to control motion. By changing the speed of each rotor, it is possible to specifically generate a desired total thrust; to locate for the centre of thrust both laterally and longitudinally; and to create a desired total torque, or turning force.

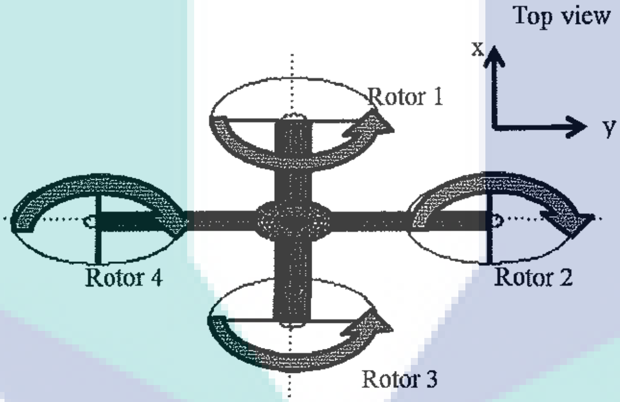

Figure 2: The direction of propeller's rotation

Rigid aircraft space movement can be divided into two parts: the center of gravity movement and the center of gravity around the movement. Any time space movement can be described using six degrees of freedom. The six degree degrees of freedom consist of three centroid movements and three angular movements, namely three translations along three axes and three rotational movements. The movement includes forward, backward, lateral, vertical, roll, pitch and yaw movement. The deflection motion of the four rotors can be achieved by the reaction torque generated by the rotor. The size of reactive torque is relative to the rotor speed.

When four rotors speeds are the same, the reaction torque will be balanced with each other, and hence, the quadrotor will not rotate. In contrast, if the four rotors speeds are not exactly the same, the reaction torque will be unbalanced and the four rotators will begin to rotate. Since there are four inputs and six outputs, quad-rotor is considered as an under actuated nonlinear composite systems. In order to control it, some assumptions were made during the four-rotor modeling:

a) the four-rotor was rigid;
b) the structure was symmetrical;
c) the ground effect was neglected.

2.2 Mathematical Modeling of Quad-rotor

Quad-rotor basically moves in translational and rotational motion. Thus specific system inputs will affect each state. Shown below, the configurations of quad rotor dynamic system connections:

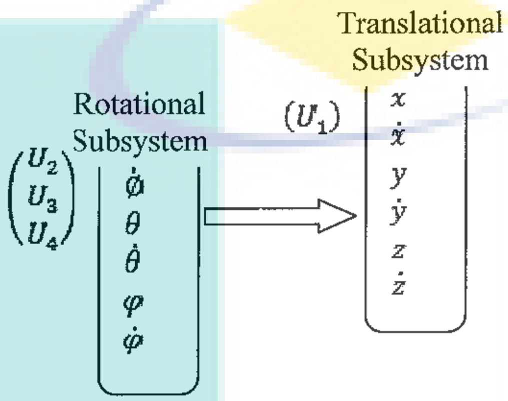

Figure 3: Relationship of system inputs to quad-rotor subsystem

Degree of freedom of quad-rotor system architecture can be simplified based on equation of motion. Newton Euler Formalism is used to obtained force and torque applied that will be important to derived the quad-rotor dynamics.

Newton Euler Formalism state that,

$$F = ma \qquad , \qquad \tau = I\alpha$$

Referring to the mass and inertia expressed in Quad-rotor frame below, the force for each translational and rotational movement is simplified.

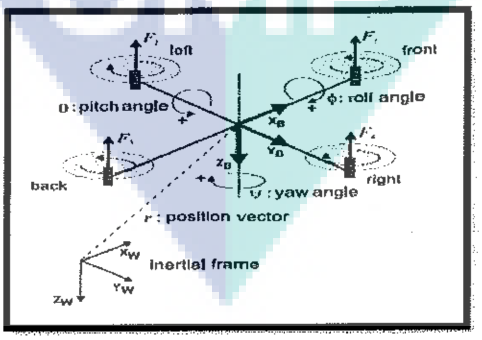

Figure 4: Quad-rotor Frame

$$\begin{bmatrix} F_x \\ F_y \\ F_z \end{bmatrix} = \begin{bmatrix} m & 0 & 0 \\ 0 & m & 0 \\ 0 & 0 & m \end{bmatrix} \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} \tau_x \\ \tau_y \\ \tau_z \end{bmatrix} = \begin{bmatrix} I_{xx} & 0 & 0 \\ 0 & I_{yy} & 0 \\ 0 & 0 & I_{zz} \end{bmatrix} \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} \tag{2}$$

Based on Table 1, know that Quad-rotor consists of 12 states. The equation of motion derived must be referred on all of the state involved.

$$\dot{X} = [x \quad \dot{x} \quad y \quad \dot{y} \quad z \quad \dot{z} \quad \emptyset \quad \dot{\emptyset} \quad \theta \quad \dot{\theta} \quad \varphi \quad \dot{\varphi}]^T \tag{3}$$

Table 1: State representation

Parameter	State Variable
$x_1 = x$	Motion along X axis
$x_2 = \dot{x_1} = \dot{x}$	Velocity along X axis
$x_3 = y$	Motion along Y axis
$x_4 = \dot{x_3} = \dot{y}$	Velocity along Y axis
$x_5 = z$	Motion along Z axis
$x_6 = \dot{x_5} = \dot{z}$	Velocity along Z axis
$x_7 = \phi$	Angular Roll
$x_8 = \dot{x_7} = \dot{\phi}$	Angular Roll rate
$x_9 = \theta$	Angular Pitch
$x_{10} = \dot{x_9} = \dot{\theta}$	Angular Pitch rate
$x_{11} = \psi$	Angular Yaw
$x_{12} = \dot{x_{11}} = \dot{\psi}$	Angular Yaw rate

Rotation matrix can be obtained from homogenous transformation matrix, where involved all degree of freedom of quad-rotor. Noted that quad-rotor consist of 12 states but with only 6 degree of freedom. Each degree of freedom will form a $\boldsymbol{Denavit - Haternberg\ Algorithm}\ (D - H)$ homogenous transformation matrix before being multiplied to each other to form overall transformation matrices of quadrotor. Given in equation (4) is the basic form of D-H homogeneous transformation matrices.

$$T_{i-1}^{i}=\begin{bmatrix} C\theta_i & -S\theta_i C\alpha_i & S\theta_i S\alpha_i & \alpha_i C\theta_i \\ S\theta_i & C\theta_i C\alpha_i & -C\theta_i S\alpha_i & \alpha_i S\theta_i \\ 0 & S\alpha_i & C\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad (4)$$

where $S\theta_i$ and $C\theta_i$ are $Sin\,(\theta_i)$ and $Cosine\,(\theta_i)$, respectively. Rotational matrix ,$R_0^k(q)$ is a part of the homogenous transformation matrix as shown in equation (5). Thus, the rotational matrix can be obtained from the formed of homogenous transformation matrix.

$$T_{i-1}^{i}=\left[\begin{array}{ccc|c} & R_0^k(q) & & p_0^k(q) \\ -- & -- & -- & --- \\ 0 & 0 & 0 & 1 \end{array}\right] \qquad (5)$$

Quad-rotor rotation matrix obtained is,

$$R_0^6=\begin{bmatrix} C_\theta C_\varphi & S_\phi S_\theta C_\varphi - C_\phi S_\varphi & C_\phi S_\theta C_\varphi - S_\phi S_\varphi \\ C_\theta C_\varphi & S_\phi S_\theta S_\varphi + C_\phi C_\varphi & C_\phi S_\theta S_\varphi - S_\phi C_\varphi \\ -S_\theta & S_\phi C_\theta & C_\phi C_\theta \end{bmatrix} \qquad (6)$$

All of the matrix form above is used in derivation of Quad-rotor dynamic by substituting into equation (7) and equation (8) for translational and rotational motion respectively.

$$F_B=\begin{bmatrix} 0 \\ 0 \\ -U_1 \end{bmatrix} \qquad (7)$$

$$M_B=\begin{bmatrix} lU_2 \\ lU_3 \\ U_4 \end{bmatrix} \qquad (8)$$

Simplifying this project, quad-rotor system dynamics is taken from Samir Bouabdallah paper [10]. In this paper, the dynamic system of quad rotor is written in state space form in terms of $\dot{X}=f(X,U)$ as shown in equation (9).

$$f(X,U) = \begin{bmatrix} x_2 \\ (\cos x_7 \sin x_9 \cos x_{11} + \sin x_7 \sin x_{11})(\frac{U_1}{m}) \\ x_4 \\ (\cos x_7 \sin x_9 \sin x_{11} - \sin x_7 \cos x_{11})(\frac{U_1}{m}) \\ x_6 \\ -g + (\cos x_7 \cos x_9)\left(\frac{1}{m}\right) U_1 \\ x_8 \\ x_{12} x_{10}\left(\frac{Iy - Iz}{Ix}\right) - \left(\frac{Jr}{Ix}\right) x_{10}\Omega + \left(\frac{1}{Ix}\right) U_2 \\ x_{10} \\ x_{12} x_8\left((I_z - I_x) I_y\right) - \left(\frac{Jr}{Iy}\right) x_8 \Omega + \left(\frac{1}{Iy}\right) U_3 \\ x_{12} \\ x_{10} x_8\left(\frac{Iz - Iy}{Ix}\right) + \left(\frac{1}{Iz}\right) U_4 \end{bmatrix} \tag{9}$$

where, x, y and z motions are consequence with pitch or roll motion. However, the angles do not depend on the translational components. As mentioned in Table 1, translation components covered on first six states in the equation (9), while rotational components are on the last six states and it is formed in non-linear model.

2.3 Controller Design

Quad-rotor MAV consists of 2 loops which are inner for attitude loop and outer for position loop. The controller used in this study is Proportional Differential (PD) controller. The block diagram of the system is shown in Figure 5.

In the first subsystem, two PD controllers are used in the quadrotor controller system. The first controller is the outer controller which controls the outer loop (x, y) and the second controller is the inner loop controller Roll ∅, Pitch θ, Yaw ψ and Z. These PD controller will generate 4 control inputs to the quadrotor model. These outputs are:

- u_1– The resulting thrust of the four rotors
- u_2– The difference of thrust between the motors on the x axis which results in Roll ∅ angle changes and subsequent movement in the lateral x direction.
- u_3– The difference of thrust between the motors on the y axis which results in Pitch θ angle changes and subsequent movement in the lateral y direction.
- u_4– The difference of torque between the clockwise and counterclockwise rotors which results in Yaw ψ angle and a moment that rotates the quadrotor around the vertical z axis.

The output of PD controller in quadrotor will directly affect the inputs. Since quadrotor only consist of 4 control inputs, we design the controllers such that it is able to stabilize the desired x, y, z positions and heading. The equations of the net thrust and torque equations to define the control inputs u of the four rotor systems.

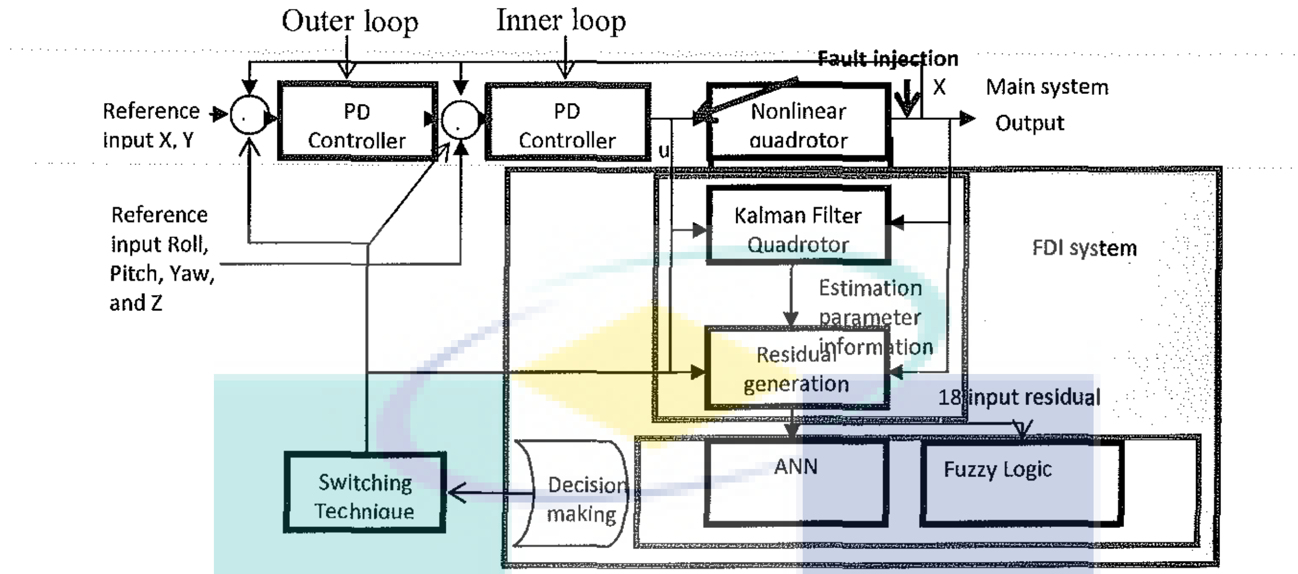

Figure 5: Block Diagram of quadrotor model with two control loop

2.4 Design of Bank of Kalman filter for residual generator

In this research, the linear Kalman filter is needed to perform a nonlinear Kalman filter in a nonlinear system. It uses information from both the state space model of nonlinear quadrotor system and state space of the linearized system.

A suitable observer for quadrotor system is possible by considering the general Kalman Filter equation, assuming that any types of faults may occur at any location, and by assuming that the number and types of potential faults need not be the same for each fault location.

The general equation of the Kalman filter:

$$\hat{X}_k = A(\hat{X}_{k-1}) + B(u) \tag{10}$$

$$P = APA^T + Ex \tag{11}$$

$$K = PC\left(inv(CPC^T + Ez)'\right) \tag{12}$$

$$\hat{X}_k = \hat{X}_k + K\left(X_k - C(\hat{X}_k)\right) \tag{13}$$

$$P = \left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - KC\right)P \tag{14}$$

where X_k is the x output value on each k in second. $\hat{X}_k$ is the state estimate value of X_k. P is the estimate covariance, K is the Kalman gain, Ex and Ez are the covariance of sensor and actuator, respectively.

A complex nonlinear quadrotor system will require a bank of kalman filter for maintenance and time prediction. The kalman filters developed in the nonlinear system are used to identify and predict the output of the $\dot{\phi}$, $\dot{\theta}$, $\dot{\psi}$, ϕ, θ, and ψ of quadrotors.

2.4.1 Linearization

Considering that linear kalman filter is used in the non-linear quadrotor model, linearization is needed. to predict the state condition, X.

The linearization is developed around the equilibrium point, in this case is hovering condition.

Since the function $\hat{f}$ in equation (9) is nonlinear, the problems arises requires unique solution for the system. In particular, the solution is difficult to find in closed form because the trigonometric functions are related to each other in no-elementary way. For this reason, the linearization is performed on a simplified model with small oscillations. This simplification is made by approximating the sine function with its argument and the cosine function with unity.

This particular value represents the force necessary to delete quadrotor's weight on its hovering condition. After determined the equilibrium point $\bar{x}$ and the corresponding nominal input $\bar{u}$, we obtain the matrices associated to the linear system. The relations are as follows:

The state space in equation is written as follow:

$$A = \begin{bmatrix} \frac{df_1}{dx_1} & \cdots & \frac{df_1}{dx_{12}} \\ \vdots & \ddots & \vdots \\ \frac{df_{12}}{dx_1} & \cdots & \frac{df_{12}}{dx_{12}} \end{bmatrix} \tag{15}$$

$$B = \begin{bmatrix} \frac{df_1}{du_1} & \cdots & \frac{df_1}{du_4} \\ \vdots & \ddots & \vdots \\ \frac{df_{12}}{du_1} & \cdots & \frac{df_{12}}{du_4} \end{bmatrix} \tag{16}$$

Linearization in nonlinear model in the state space mode is shown as follows:

$$\dot{X} = AX + Bu \tag{17}$$

$$Y = C\dot{X} \tag{18}$$

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & g & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -g & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{19}$$

$$B = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \frac{1}{m} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & \frac{l}{l_x} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{l}{l_y} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{l_z} \end{bmatrix} \tag{20}$$

Under normal circumstances, matrix of A, B, C and D in Kalman Filter should be in constant format. The state A is updated to form A linearize and is the same as the state B updated to B linearize due to the linear kalman filter is used in the state itself, therefore linearization are used here to demonstrate that it updates the system from filter to prediction.

2.4.2 Residual Generation

The fault diagnosis scheme used here is based on a group of observation where every observer is exclusively associated to a sensor. Each observer has an input signal *u* and the output of its corresponding sensor. The observer output provides an estimation of its associate sensor. Using the estimated value of Kalman Filter, the residuals are generate for each real and predicted measurement of acquired input and output,

$$r = y - \hat{y} \tag{20}$$

$$\begin{cases} Re1(t) = \emptyset(t) - \hat{\emptyset}(t) \\ Re2(t) = \theta(t) - \hat{\theta}(t) \\ Re3(t) = \psi(t) - \hat{\psi}(t) \\ Re4(t) = X(t) - \hat{X}(t) \\ Re5(t) = Y(t) - \hat{Y}(t) \\ Re6(t) = Z(t) - \hat{Z}(t) \end{cases} \tag{21}$$

where, r is the residual vector, y is the real measurement vector and $\hat{y}$ is the estimated measurements vector.

The 6 residual generated for the system are $Re1 - 6$. Re1 is residual of Roll ($\emptyset$), $Re2$ is residual of Pitch (θ), $Re3$ is residual of Yaw (ψ), $Re4$ is residual of X position, $Re5$ is residual of Y position and $Re6$ is residual of Z position. The output Residual vector in equation (21) is used to generate each of residual (Re) signal. The residual values are then fed into the fault system unit, using ANN to identify the fault type.

2.5 Neural network design

The ANN model used in this experiment is shown in Figure 6. The fault should be predicted from detecting, isolating, and identifying the severity of a failure in the presence of disturbances and uncertainties in model and sensor measurements. The neural network weights are updated based on a modified dynamic Nonlinear Autoregressive Network with Exogenous Inputs (NARX) scheme. The proposed FD scheme does not depend on the availability of full state measurements. In most of the work in the literature, the fault function acts as an additional term on the actuator, where the fault acts as a multiplication term.[11] This will provide an extraordinary and challenging analysis of the stability and convergence of the entire FD program.

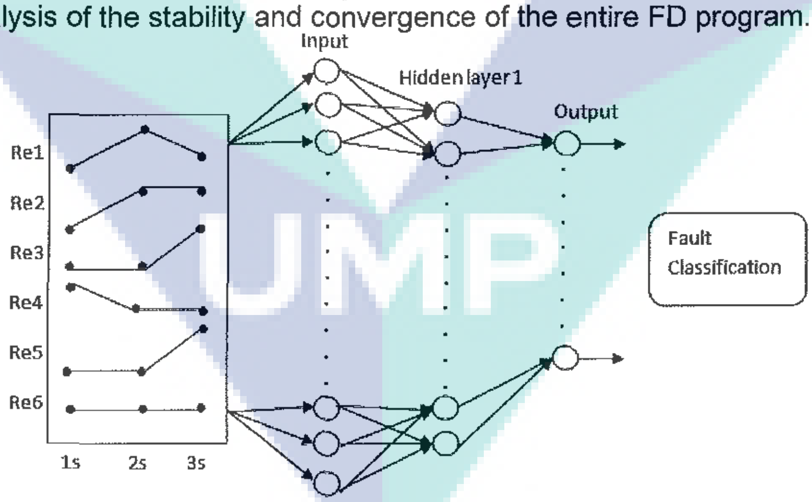

Figure 6: ANN model with 18 input neuron from residuals, 20 hidden neuron and 10 output for fault classification

ANN uses Nonlinear Autoregressive Network with Exogenous Inputs (NARX) training process to find the appropriate weight for each network. $Re1, Re2, Re3, Re4. Re5$ and $Re6$.

The type of faults that will be detected are Roll(ø) fault, Pitch (θ)fault, Yaw (ψ) fault, X fault, Y fault, Z fault, rotor 1 fault, rotor 2 fault, rotor 3 fault and rotor 4 fault. Roll(ø), Pitch (θ), Yaw (ψ), X, Y and Z fault are considered as sensor faults. Meanwhile, rotor 1, rotor 2, rotor 3 and rotor 4 fault are considered as the actuator faults.

The fault diagnosis scheme is based on a group of observation where every residual is exclusively associated to the sensor. Each residual has 3 inputs which are the magnitude of the residual, the signal in time *(t-1)* and the signal in time *(t)*.

In this research, the learning phase process of ANN has been feed with 25839 data, from various types of fault generated by quad-rotor model under Matlab Simulink. This knowledge based data allows the weight link between neuron to be updated to produce a closer output based on the conclusion of all set of data that have been trained. The matrix input 25839x18 representing static data of 25839 sample of 18 elements and output train target value matrix 25839x10 representing static data of 25839 samples of 10 elements are saved in the form of excel format.

Among the 18 input elements, the residual generation will generate 6 residuals and each residual will be divided into 3 inputs and thus a total of 18 inputs will be fed to the hidden layer. 10 elements of output refer to the corresponding 10 types of fault that can be detected simultaneously by the system.

Based on the sample available in information data, we set the training, validation and testing percentage as follows:

For a randomly divide up to the 258390 sample:

- Training : 70 percent (180872 sample)
- Validation : 15 percent (38759 sample)
- Testing : 15 percent (38759 sample)

The training section is firstly represented in the network during training and the network is adjusted according to its error. Next, validation is used to measure network generalization and halt training when generalization stops improving. Lastly, the testing stage is to provide an independent measure of the network performance during and after training.

3. LITERATURE REVIEW

Fault Detection and Isolation (FDI) is commonly used in different aeronautic and navigation applications such as aircraft elevator control system and car engine diagnosis. It allows the system to identify the type of fault, the location of the fault and to reduce unnecessary procedures time. It also allows the user to monitor, observe and pinpointing the type of system fault and location.[12] Different approaches for fault-detection using mathematical models have been developed in the last 20 years.[2][13][14]
There are three different methods for Fault Detection and Isolation (FDI) tasks, namely, intelligence based method, mathematical based method and hybrid method.

3.1 Intelligence Based Method

Research on intelligence based FDI was done by using neural network[15], fuzzy-logic[16], neuron-fuzzy system and genetic algorithm. The biggest challenge of this FDI method is the precision problems. Most literature using this approach would assume the plant as a linear system. Generally, a linearization method is applied when dealing with nonlinear system complex system. However, there are cases where linearization is inappropriate as a linearized system cannot fully mimics the natural response of a nonlinear condition. Additionally, the computational intelligence based approaches are developed under a black box "assumption". One could not know the nature of process inside the system. When there are any unwanted performance of the system, such as oversensitive or non-sensitive to the presence of failure, the parameter cannot be adjusted easily. Thus, this approach may lead to system robust-ness problem.

3.2 Mathematical Based Method

The second FDI approach is Mathematical-Based FDI Method. It detect faults in the processes, actuators and sensors by using the dependencies between different measurable signals. These dependencies are expressed by mathematical process models. The model-based fault detection method is developed by using the input and output signals and by applying the dynamic process model. These methods are developed based on parameter estimation, parity check equations, or state observers. The goal is to generate several symptoms that indicate the difference between nominal and faulted states. Faults are identified by applying classification or inference according to the different symptom diagnostic procedures.[17] The generation of residual signals is the core element of model-based fault detection.[3] The model-based approaches rely on the analytic mathematical model of the process being monitored. There are various approaches to generate the residues including estimating the system fault, such as local model thresholds (LMT) [12], parity space approach[13], fault detection filter, observer-based method[20], sliding mode observer[18], adaptive observer[19], $H\infty$ filter approach[3]. However, these approaches have limitations in deriving an accurate mathematical model of the complex system and hence making researcher difficult to obtain the accurate model parameter value. Additionally, some systems exhibit uncertain behaviours such as higher order dynamic and high-frequency oscillations, collectively called as unmodeled dynamics, which cannot be precisely modelled.

3.3 Hybrid Method

The third approach, the Hybrid Based FDI Method, is a combination of the Model-Based FDI Method and Computation Intelligence Based FDI Method. This method can measure the faults that cannot be detected using solely the first method and the second method. Because of this special function, the Hybrid Based FDI Method offers more versatility and mobility. As such, it is able to predict parts that are not detected by the sensors, especially in the context of sensor or actuator or both.

4. FINDINGS

The proposed method is tested by using scenario as illustrated in Figure 7.
To emulate this fault, the concept of this Hybrid FD technique is developed by comparing the Kalman filter with the virtual real system to obtain the residual information.
Assumptions:

- Roll (ϕ) = 1 rad ≈ 57.2958degree (MAX angle of rotation)
- Pitch (θ) = 1 rad ≈ 57.2958degree (MAX angle of rotation)
- Yaw (Ψ)= 0 rad
- Location to travel: (10 (X location),10(Y location), 10(Z location)) start from initial (0, 0, 0) meter in unit