Wind Estimator Using Attitude Measurement From Quadrotor Flight Under Wind Disturbance

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***Abstract*— There is a limitation to flying a quadrotor in the lowest layer of the atmosphere, the troposphere level. Thus, it is difficult to evaluate the performance of the quadrotor under the presence of wind. The main objective of this project is to validate the quadrotor control performance under the proposed wind prediction model. A wind estimator model was designed using neural network models to validate the quadrotor model with a proportional integral derivative(PID) controller, flying under external disturbance. The performance of the wind estimator model was evaluated based on error measurement. Thus, the actual flight data and the estimated data were compared and evaluated to obtain the best performance for the quadrotor flight control. The simulation results of the wind estimator signified that the model has been successfully developed according to the set parameters. Thus, the outcome of this project shows that neural network fitting can be embedded inside the quadrotor and work together with the existing PID controller to control the quadrotor in a robust environment.**

Keywords—wind estimator, quadrotor control, neural network fitting

I. INTRODUCTION

Unpredictable wind gust appears within the troposphere level that can degrade the stability of quadrotor flight. Despite many advantages of unmanned aerial vehicles (UAV), there are also many challenges depending on the design and quadrotor efficiency. The vertical and horizontal movement of the quadrotor in the air is highly affected by wind disturbance. In general, the horizontal and vertical components of wind direction play a larger role in roll disturbances[1]. Several existing studies have been reported to solve the wind disturbance problems such as using a control approach, actual flight testing inside a wind tunnel, and estimation of wind using the black box technique[2]. Better flight performance can be obtained by taking into account the wind disturbance characteristics.

Fig. 1 shows the quadrotor features six degrees of freedom (DOFs), including x, y, and z for translational motions and roll (φ), pitch (θ) and yaw (ψ) for rotational motions, and only four propellers (inputs) for throttle, roll, pitch, and yaw motions. Fig. 2 shows the gap analysis from 2018 for the application of machine learning to be embedded with the quadrotor model to improve its capabilities. A research paper from the University of

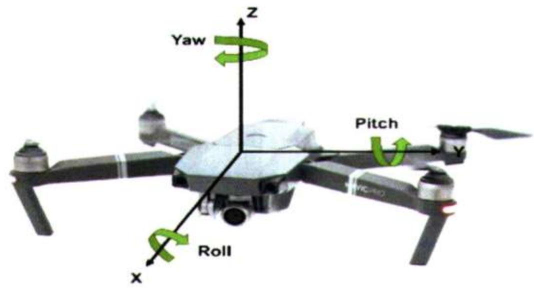

Fig. 1. Diagram of Euler angle for a quadrotor.

Guadalajara, Mexico proposed a study about proportional integral derivative (PID) controller for a quadrotor based on an Artificial Neural Network (ANN) in 2018 [3]. The simulation and experimental result show that the PID neural network (PIDNN) can follow the trajectory and shows a faster response thus able to control in real-time.

A work done by [4] in 2019, proposed a wind estimation using K-Nearest Neighborhood (KNN) which does not require details of the aerodynamic information. Estimation from a drone and proposed KNN were compared to real wind speed and the results show that KNN was closer to the result of the real wind speed up against from drone.

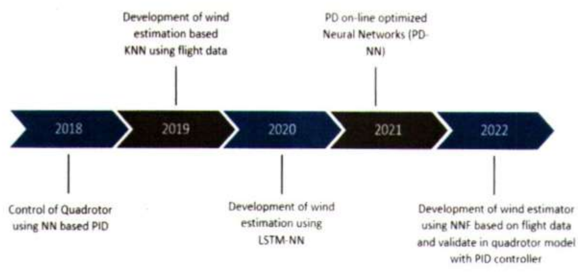

Fig. 2. Gap analysis based on neural network

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In the year 2020, a publication from Vertical Flight Society's 76th Annual Forum and Technology Display proposed a machine-learned black box trajectory generator[5]. In order to validate the performance of the generator, the root mean square error between actual trajectories and neural network (NN) generated trajectories has been evaluated in the paper. In the same year, a group of Oklahoma researchers used miniature unmanned aerial systems (sUAS) to study the problem of wind estimates in atmospheric turbulence [6]. The study was conducted to estimate the turbulent winds generated by the Dryden gust model. This paper compared the long short-term memory neural network (LSTM-NN) with the wind triangle in both mean error and variance.

A publication from the International Review of Applied Sciences and Engineering in 2021, proposed a PID controller with back propagation neural network with wind gust rejection for quadrotors [7]. This paper aim is to evaluate proportional derivative (PD) and PD with optimized NN (PD-NN) control techniques in the presence of various levels of wind disturbances. As the result, the PD-NN controller follows all the trajectories with any constraint and allows for improvement in the responses whether in applying the wind disturbance with different degrees.

This paper presents the development of a wind estimation model for a quadrotor aerial vehicle using well known artificial intelligence (AI) technique called Neural Network Fitting (NNF). Dataset used in the model development phase is obtained from the actual quadrotor UAV flying under turbulence wind that was conducted in a wind tunnel lab environment. The wind estimation model will be added to the quadrotor model using SIMULINK to analyze quadrotor performance under wind disturbance. The performance will be validated with the quadrotor UAV flying under turbulence wind from the experimental result.

The supervised learning method for Multilayer perceptron (MLP) feed forward neural network (FFNN) is using back propagation (BP) algorithms. Calculations begin at the output layer for this purpose, then propagate backward until each weight connection may be adjusted. The structure of a layered network is a combination of the input layer, hidden layer and output layer as seen in Fig. 3.

In this project, there were four input and one output is been used. The input used were roll, pitch, yaw and control torque while the output is position Y where the number of hidden layers used was 14. Usually, the activation function used in ANN is the sigmoid function.

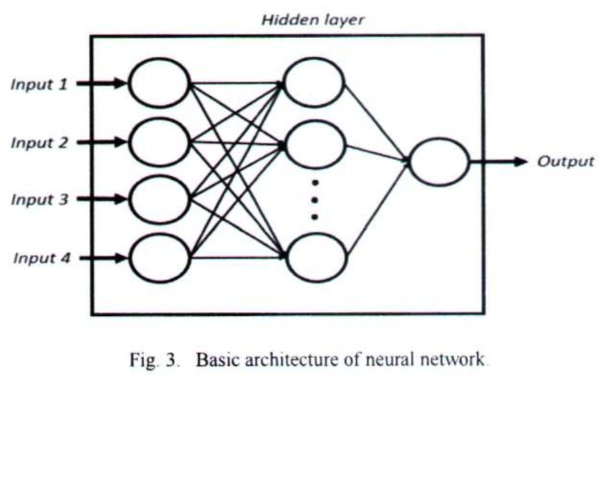


Fig. 3. Basic architecture of neural network

There are three training algorithms for the training of the data such as Levenburg-Marquardt (LM), Scaled Conjugate Gradient (SCG) and Bayesian Regularization (BR). In order to train and identify the model parameter selection and measure the model prediction error or accuracy, the data is usually divided into training and validation sets. The learning phase analyses the training set to create a mathematical model that represents the set, while the validation set is used to verify its performance. At this part, if the result of performance was not acceptable, then it will return to the learning phase to adjust the algorithm parameter to revise the model. Once the validation was at an acceptable level, then the model will be evaluated in the test set.

II. METHODOLOGY

This section discussed about the flow of the project to achieve the objectives. An overall flowchart was shown in Fig. 4. This project mainly has three tasks, which are constructing the quadrotor model, developing the wind estimator and validating the performance under wind disturbance.

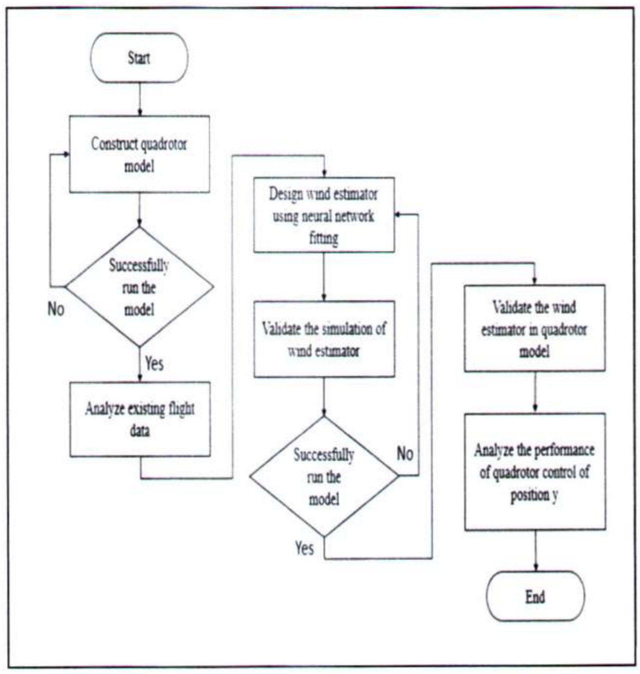


Fig. 4. Overall project flowchart

A. Development of Quadrotor Model

This project started with the construction of the quadrotor model using SIMULINK with the actual flight data testing under wind tunnel. The nonlinear of quadrotor model was built from the Bouabdallah model[8]. The mathematical model of the quadrotor model was formulated using Newton-Euler equation.

TABLE I
Parameter Of Quadrotor Model

Parameter	Description	Value
Ix	Quadrotor moment of inertia around X axis	7.5*10^(-3)
Iy	Quadrotor moment of inertia around Y axis	7.5*10^(-3)
Ix	Quadrotor moment of inertia around Z axis	71.3*10^(-2)
Jr	Total rotational moment of inertia around the propeller axis	6.5*10^(-5)
b	Thrust factor	3.13*10^(-5)
d	Drag factor	7.5*10^(-7)
l	Distance to the center of the quadrotor	0.23
m	Mass of the quadrotor in kg	0.65
g	Gravitational acceleration Parameter	9.81

B. *Development of Wind Estimator*

The wind estimator model is constructed using Neural Network Fitting as shown in Fig. 5. The dataset is divided into three groups which are training, validation and testing. Before the data was trained, the training algorithm must be selected. Three training algorithms included in this study are Levenburg-Marquardt, Scaled Conjugate Gradient and Bayesian Regularization. Comparison between these three algorithms helps in choosing the best training algorithm for the wind estimator before further validation in the quadrotor model.

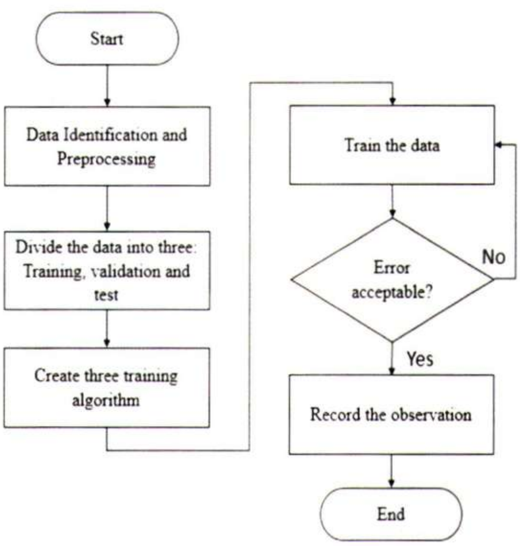


Fig. 5. Development of wind estimator using NNF.

The input and target data should be chosen before the data is applied to the neural network. The input data in this case are roll, pitch, yaw, and control torque, with position Y as the target. Both input and output were obtained from actual flight data. Data preprocessing is essential for highly noisy actual flight data. Fig. 6 shows roll, pitch, and yaw data before and after filtering. Data preprocessing promotes high accuracy and lower computational costs throughout the learning phase. This project selected a moving average filter as the data preprocessing. Thus, the preprocessing data was fed into the NN process in order to construct the wind estimator NNF model in SIMULINK.

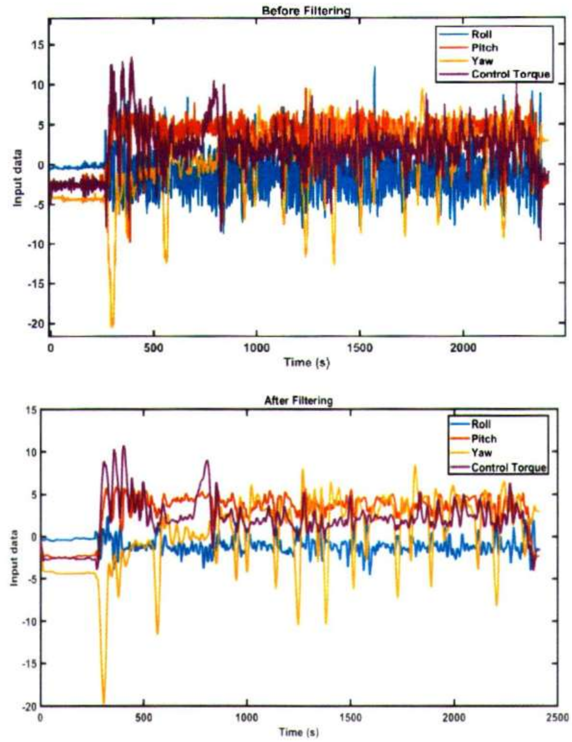


Fig. 6. Roll, pitch and yaw data before (above) and after (below) filtering.

C. *Wind Estimator Validation*

After developing the wind estimator model using NNF, the model was then evaluated with the actual flight data from the quadrotor model with the PID controller. Then, the output from actual flight data will be compared to the output obtained from the NNF wind estimator algorithm.

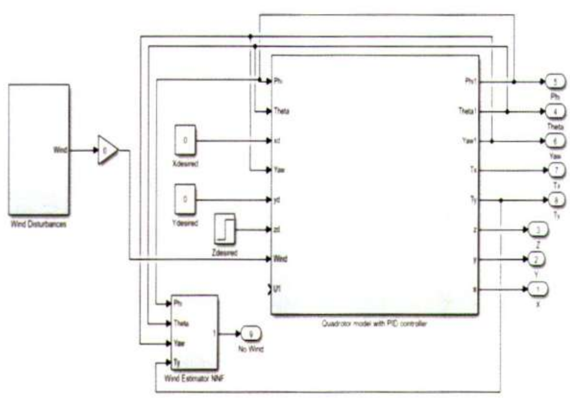
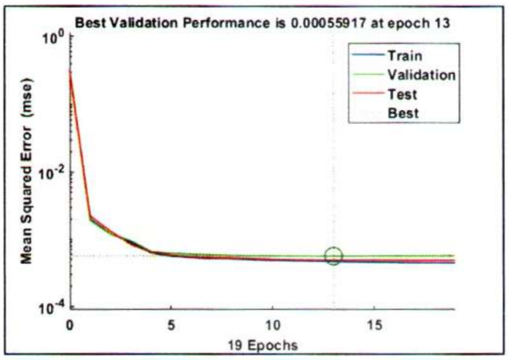


Fig. 7. Quadrotor model equipped with smart PID controller together with wind estimator NN in SIMULINK.

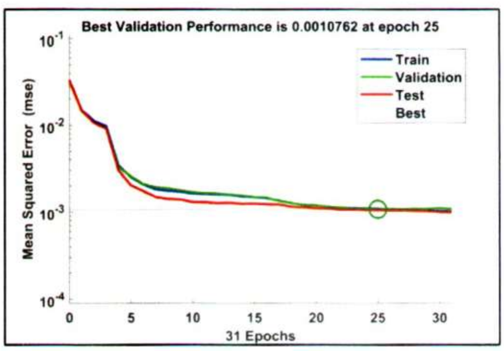
III. RESULTS & DISCUSSIONS

A. Training Performance using different Algorithms

(a)



(b)



(c)

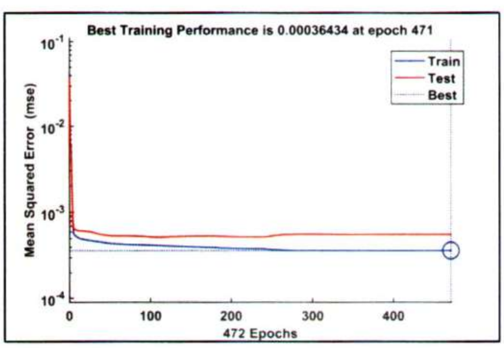
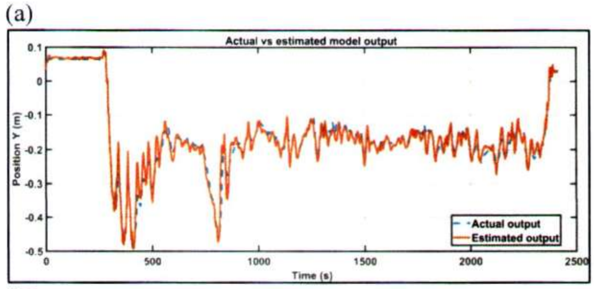


Fig. 8. Training performance using (a) Levenburg-Marquardt (LM), (b) Scaled Conjugate Gradient (SCG) and (c) Bayesian Regularization (BR) algorithm.

Fig. 8 shows that LM had the best validation performance of 5.59E-4 achieved at epoch 13. The BR algorithm had a training performance of 3.64E-4 achieved at epoch 471, and SCG of 1.08E-3 achieved at epoch 25. Based on observation of graphs in all three figures shows that the BR algorithm takes more epochs to get the best results compared to LM and SCG, but it has less mean squared error (MSE) compared to the other learning algorithms. The SCG algorithm is the lowest regarding performance and takes more epochs than LM to train.

B. Validation of Wind Estimator

(a)



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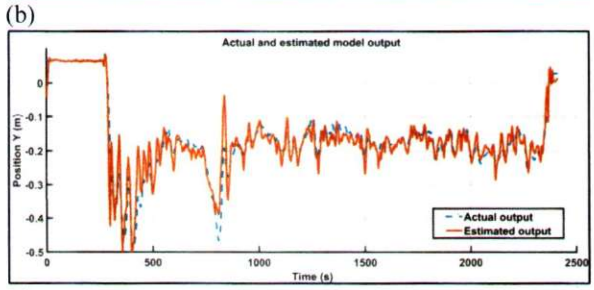

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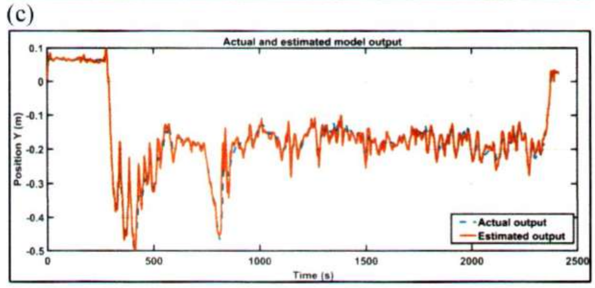

Fig. 9. Performance comparison using (a) Levenburg-Marquardt, (b) Scaled Conjugate Gradient and (c) Bayesian Regularization algorithm.

Based on Fig. 9, the predicted curve that almost overlaps with the actual output is BR and LM algorithm. Estimated output with a highly similar to the actual output curve leads to a good performance result. It is shown that SCG estimated output had deviated away at a particular range. Thus, the lesser the MSE, the higher the accuracy of the performance.

C. Validation Estimation in Quadrotor Model

Two types of controllers were compared which are the classical controller (linear PID controller) and the proposed controller (PID controller with NNF) as shown in Fig. 10 until Fig. 12. The performance of quadrotor using these two types of controllers is analyzed at two conditions which are without wind disturbance and with the presence of wind in Fig. 10 until Fig. 12.

In Fig. 10(i), the response of both controllers toward wind gusts is presented. The quadrotor is hovering at time 0 to 200sec and the wind gust appeared at time 0 to 40sec. The performance of the classical controller and proposed controller are shown in Fig. 10(i) and Fig. 10(ii), respectively. Based on the figures, it can be concluded that the quadrotor performs well using the proposed controller when the steady-state error is smaller compared to the steady-state error using the classical controller.

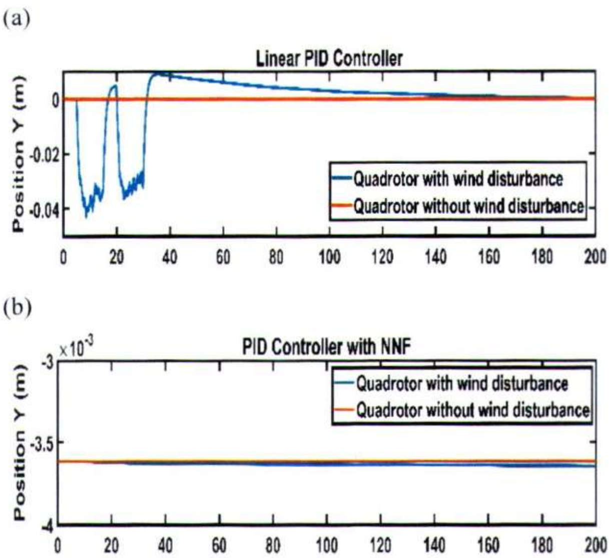

Fig. 10. Quadrotor hovering from 0 to 200sec with wind gust disturbance appeared from 0 to 40sec using classical PID controller (a) and proposed PID controller (b).

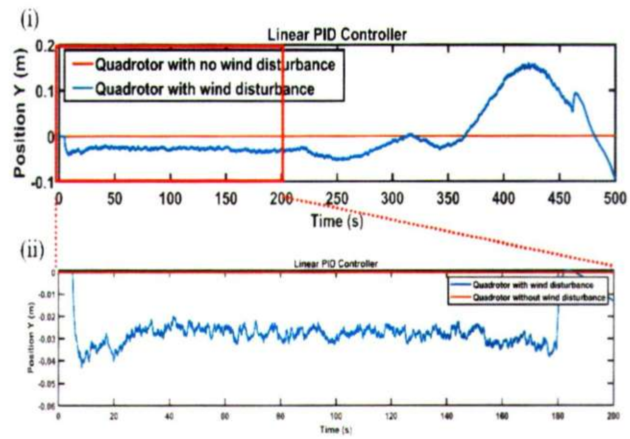

Fig. 11. Quadrotor hovering from 0 to 500sec with constant wind disturbance appeared from 0 to 200sec using classical PID controller.

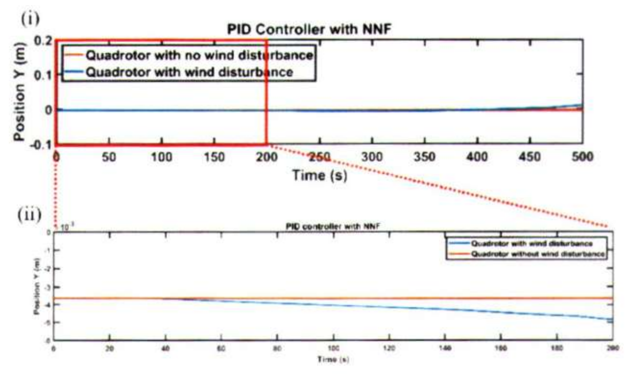

Fig. 12. The quadrotor is hovering from 0 to 500sec with constant wind disturbance appearing from 0 to 200sec using the proposed PID controller.

Next, the performance of the proposed controller is tested inside the quadrotor under the presence of constant wind as shown in Fig. 11. The performance of the quadrotor using the classical controller is shown in Fig. 11 and the performance of the quadrotor using the proposed controller is shown in Fig. 12.

Based on the figure, it can be concluded that the proposed controller is able to drive the quadrotor to the desired position and the performance is almost similar when the quadrotor is without wind disturbance. Unlike classical quadrotor in Fig. 11, the constant wind results in the quadrotor deviating from the desired position with the displacement error is 0.04E-3m as shown in Fig. 12(ii).

Meanwhile in Fig. 12(i), the wind disturbance is continuously presence from 0 to 500sec. The performance of the proposed controller shows that, despite the constant wind disturbance, the controller is able to drive the quadrotor near to the desired position. However, for classical PID controller is unable to drive the quadrotor closer to the desired position compared to the proposed PID controller.

IV. Conclusions

In conclusion, the comparative had been performed in order to determine the best performance in developing the wind estimator. Among the other algorithms, SCG had the lowest performance. SCG, on the other hand, was the fastest in terms of speed. In terms of accuracy, BR surpasses LM and SCG. Depending on the statistics, it is clear that BR outperformed other algorithms in terms of MSE and R. LM, on the other hand, is the greatest option because it is more accurate than SCG and requires less time than BR. As a result, LM has been chosen as the training algorithm due to its high accuracy and speed.

NNF model can learn and act like intelligent human behaviour. NNF can be embedded inside the quadrotor and work together with the existing PID controller to control the quadrotor in a robust environment. This technology may assist in applications such as agriculture, especially in corps farming. This quadrotor model is able to hover in strong wind conditions in open areas. This modern technology can be adopted by drones to help in monitoring for agriculture. Also, NNF helps in maintaining sustainability. For future recommendation, this research can proceed with developing a wind prediction model and validate under strong wind disturbances in real time condition.

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