PROGRESS IN AEROSPACE AND AVIATION TECHNOLOGY
e-ISSN: 2821-2924

PAAT

Vol. 5 No. 1 (2025) 28-40
https://publisher.uthm.edu.my/ojs/index.php/paat

System Identification Study for A Small-Scale Hybrid Unmanned Aerial Vehicle Using Differential Evolution Approach

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DOI: https://doi.org/10.30880/paat.2025.05.01.004

Article Info

Received: 15 January 2025
Accepted: 21 May 2025
Available online: 30 June 2025

Keywords

System identification, unmanned aerial vehicle (UAV), hybrid UAV, differential evolution

Abstract

This research develops a dynamic model for a small-scale hybrid unmanned aerial vehicle (UAV) using the system identification approach, optimized by the Differential Evolution (DE) method, aiming to enhance the performance, stability, and controllability characteristics of this complex type of UAV. The methodology involved gathering data from simulated tests using LabVIEW and X-Plane 9, establishing the model structure, and then refining and training the model parameters. The differential evolution algorithm was applied in the tuning phase, comprising initialization, mutation, crossover, and selection, to efficiently optimize parameters for precision and performance. Flight data was collected from simulated hover and forward flight tests. The training dataset employed frequency-swept excitation, while the test dataset utilized doublet excitation for validation. Model validation was conducted through statistical analysis, demonstrating high prediction accuracy. The dynamic models demonstrated low mean square error with minimal standard deviation, and the predicted responses aligned closely with measured data, confirming robustness and accuracy. This study successfully applied the DE algorithm based on the system identification approach to develop and validate accurate dynamic models for a small hybrid UAV. The results establish a valuable framework for improving UAV performance and inspiring further advancements in system identification.

1. Introduction

The hybrid UAV configuration, such as the quadplane, is a new hybrid airframe designed with the fixed-wing UAV as the main airframe with additional multirotor arms. This airframe will benefit from Vertical Take-off and Landing (VTOL) and the long range of a fixed-wing UAV. However, compared to multi-rotors, the aerodynamics, dynamics modeling, and control of the hybrid UAV are significantly more complex due to the existence of the wings and fuselage. With the development of new platforms for UAVs, modeling and control problems have arisen due to their dynamic stability.

A fundamental requirement for the effective deployment and control system design of autonomous vehicles like small-scale hybrid UAVs is the availability of an effective and simple mathematical representation of their system dynamics [1]. However, modeling these systems is a non-trivial task due to their complex dynamic features, inherent nonlinearities, instability, and the high degree of coupling among their state variables [2]. Challenges also arise when the vehicle deviates significantly from nominal operating conditions, such as hover [3]. Accurate modeling is important when predicting UAV behavior.

Various approaches have been adopted for modeling small-scale helicopter and multi-rotor systems. These generally fall into three categories: the first principle approach (often referred to as white models), the parametric approach based on system identification (grey models), and the non-parametric approach (black box models) [2]. The first principle approach involves deriving a mathematical model using fundamental laws of mechanics and aerodynamics, which can lead to high-order coupled nonlinear models useful for simulation but requiring rigorous validation against real flight data [4]. System identification uses input-output data to derive mathematical models or directly design controllers, offering versatility for analyzing, simulating, and controlling dynamic systems [5]. System identification methods include parametric techniques, which use predefined mathematical models to estimate parameters [6], and non-parametric techniques, which directly model system responses without assumptions about input-output relationships [7]. Linear models, such as ARX, are computationally efficient but may lack accuracy for highly nonlinear UAV dynamics, while nonlinear models like NARX or ANNs provide greater fidelity at higher computational costs [8]. Open-loop identification simplifies modeling by excluding feedback but may miss system stability aspects, whereas closed-loop identification incorporates feedback for more accurate real-world applications [8]. Time-domain techniques analyze temporal system behavior, while frequency-domain techniques study signal composition in terms of frequency, both offering complementary insights [9]. For model-based control applications, both the first principle and parametric system identification approaches yield the necessary mathematical representations.

Optimization methods, including Differential Evolution (DE), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO), have been applied to system parameter identification and control design to overcome these issues [10], [11]. Differential Evolution is a population-based algorithm known for its effectiveness in finding global minimums, rapid convergence, and requiring relatively few control parameters [2]. It operates through initialization, mutation, crossover, and selection processes. Leveraging the search optimization strength of DE can aid in parameter estimation for system identification, particularly for complex dynamics. Based on this background, this research aims to create a dynamic model for a hybrid UAV using a system identification method, which will be improved with the differential evolution algorithm. This approach is motivated by the need for a robust model that accurately captures the UAV's complex dynamics under various operating conditions and the ability of DE to enhance the accuracy and robustness of parameter estimation compared to conventional methods. The research involves collecting and analyzing flight data obtained through LabVIEW and X-Plane 9 simulations. The dynamic model is derived using the system identification approach, with the parameter estimation process optimized by the DE algorithm.

The remainder of this paper is organized as follows: Section 2 explains the basic ideas behind data collection methods, dynamic modeling techniques, and system identification methods for hybrid UAVs. Section 3 details the model validation process, including model prediction results and the analysis of statistical metrics used to evaluate the model's performance. Section 4 provides the conclusion and the recommendations for future work.

2. Methodology

The system identification approach based on the Differential Evolution (DE) method involves utilizing the DE algorithm, an evolutionary optimization technique, to estimate the parameters of a dynamic model of a system. This approach treats system identification as an optimization problem where the goal is to determine the set of model parameters that best match the observed input-output data from the real system or a simulation. The methodology for developing the dynamic model of a small-scale hybrid UAV using the Differential Evolution (DE) approach is conducted through a structured series of steps to ensure accuracy and reliability. The process begins with data collection, where flight data is collected from simulated tests to provide a comprehensive dataset representing the UAV's behavior under various conditions. This step ensures sufficient input for accurate model development. Following this, the model structure is established, defining the mathematical equations and framework needed to capture the UAV's dynamic characteristics. The model estimation phase then used the DE algorithm to refine the model parameters to align with the gathered data, ensuring the model's predictions closely match the observed dynamics. Afterward, the model training phases further fine-tune these parameters, improving the model's accuracy and robustness in predicting the UAV's behavior. In the tuning phase, the DE algorithm is applied, incorporating key steps such as initialization, mutation, crossover, and selection to optimize the parameters efficiently. This step ensures that the model achieves a global optimum, improving both precision and performance. Finally, the model validation phase is carried out, where the trained and adjusted model is tested with separate datasets to determine its reliability and ability to predict changes in different situations. This systematic methodology ensures the development of a robust, accurate, and reliable dynamic model for the hybrid UAV.

2.1 Data Collection

The flight data for training and validating the dynamic model are categorized as training and validation datasets. Training data is used to develop dynamic models by estimating the hybrid UAV's aerodynamic terms and stability derivatives, while validation data is used to evaluate the model's accuracy and generalization ability in predicting new flight data. Input-output data from the system is collected through flight simulations performed in X-Plane 9, with data acquired via LabVIEW software through a UDP port [12], [13], [14], [15]. Frequency-swept excitation is employed for training data to excite the system across a range of frequencies. Fig. 1 shows the example excitation signals used to excite the system dynamics. Ensuring the system is well excited over the relevant frequency range is crucial. For flight dynamics and control of a quadrotor, this range might be 0.3–20 rad/s [16], [17]. During data collection, it is necessary to record both the input signals, such as the rolling torque, pitching torque, total force, yawing torque, aileron, elevator, rudder, and forward thrust commands, and the corresponding output responses of the system (e.g., angular velocities, linear velocities, and attitude angles). Finally, a low-pass filter with a 10 Hz cut-off frequency was used to remove high-frequency noise in the data.

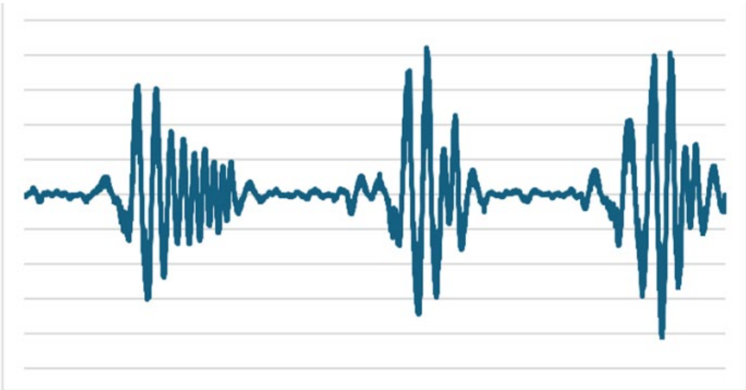


Fig. 1 *Frequency-swept data collected for training and validation*

2.1.1 UAV Model Description

The hybrid UAV model chosen for this study is the Skywalker 1900, manufactured by Skywalker. The Plane-Maker software was used to create the model on the flight simulator. With the use of a particular tool, users can create any kind of airplane they can imagine. While the X-Plane simulator forecasts the built plane's flight path, an interface called Plane-Maker allows users to construct vehicles according to the physical attributes of planes, including weight, wingspan, engine power, control deflections, and airfoil sections [18]. Fig. 2 shows the RC model, and the illustration of the UAV developed using Plane-Maker. Table 1 shows the specifications of the hybrid UAV.

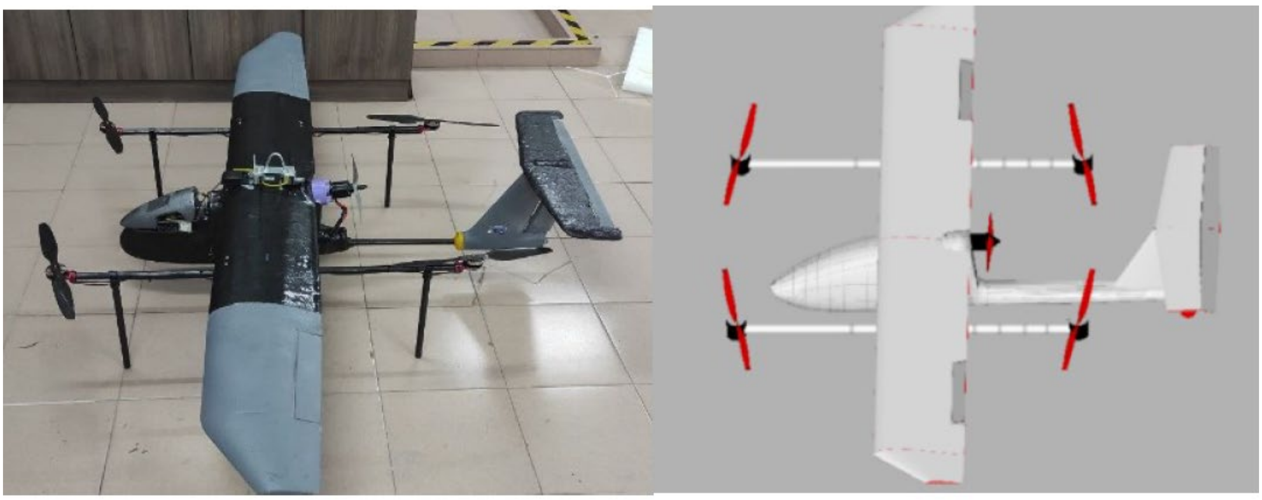


Fig. 2 *Skywalker 1900 hybrid UAV and its representation in X-plane 9 flight simulator*

Table 1 *Skywalker 1900 specifications*

Specification	Value
Model name	Skywalker 1900
Empty weight (kg)	5
Wingspan (mm)	1900
Rotor configuration	H configuration with carbon fiber arms
Electric motors	Fixed wing: SunnySky 3520 720KV
	Quadcopter: SunnySky 4008 620KV
Propeller	Fixed wing: 12x08
	Quad: 15x55
Battery	4S LiPo 5300 mAh
Altimeter	Lightware LIDAR SF/10
Inertial Measurement Unit, IMU	VectorNav VN200 + GPS

2.2 Model Structure

The dynamics of a hybrid UAV were modeled for each of its two flying modes: fixed-wing and quadcopter (VTOL) modes. Every mode has a unique representation using a linearized state-space model. The linear state space model for quadcopter mode can be expressed in the following state space equations [19]:

Longitudinal dynamic (quadcopter):

$$\begin{bmatrix}\dot{u}\\ \dot{q}\\ \dot{\theta}\end{bmatrix} = \begin{bmatrix}X_u & 0 & -g\\ M_u & M_q & 0\\ 0 & 1 & 0\end{bmatrix}\begin{bmatrix}u\\ q\\ \theta\end{bmatrix} + \begin{bmatrix}X_{ele}\\ M_{ele}\\ 0\end{bmatrix}[\tau_\theta] \tag{1}$$

where $\boldsymbol{\tau_\theta}$ is the pitch torque input, and the state variables are defined as $\boldsymbol{x_1} = [\boldsymbol{u} \quad \boldsymbol{q} \quad \boldsymbol{\theta}]^{\boldsymbol{T}}$. The states, $\boldsymbol{u}$ represent the velocity in the x-direction (body frame), $\boldsymbol{q}$ denote pitch rate and $\boldsymbol{\theta}$ is pitch angle.

Lateral dynamic (quadcopter):

$$\begin{bmatrix}\dot{v}\\ \dot{p}\\ \dot{\phi}\end{bmatrix} = \begin{bmatrix}Y_v & 0 & g\\ L_v & 0 & 0\\ 0 & 1 & 0\end{bmatrix}\begin{bmatrix}v\\ p\\ \phi\end{bmatrix} + \begin{bmatrix}Y_{ail}\\ L_{ail}\\ 0\end{bmatrix}[\tau_\phi] \tag{2}$$

where $\boldsymbol{\tau_\phi}$ is the roll torque input, and the state variables are defined as $\boldsymbol{x_2} = [\boldsymbol{v} \quad \boldsymbol{p} \quad \boldsymbol{\phi}]^{\boldsymbol{T}}$. The states $\boldsymbol{v}$ represent the velocity in the y-direction (body frame), $\boldsymbol{p}$ denote roll rate and $\boldsymbol{\phi}$ is roll angle.

Yaw dynamic (quadcopter):

$$\begin{bmatrix}\dot{r}\\ \dot{\psi}\end{bmatrix} = \begin{bmatrix}N_r & 0\\ 1 & 0\end{bmatrix}\begin{bmatrix}w\\ r\end{bmatrix} + \begin{bmatrix}N_{rud}\\ 0\end{bmatrix}[\tau_\psi] \tag{3}$$

where τ_ψ denotes the yaw torque input and the state variables are defined as $\boldsymbol{x_3} = [r \quad \psi]^T$. The states, r and ψ represent the yaw rate, and ψ denotes the yaw angle. For the heave model, the dynamic can be represented as a simple first-order system:

$$\dot{w} = Z_F F \tag{3}$$

where $\boldsymbol{F}$ is the total thrust force input, and state, w represent the velocity in the z-direction (body frame).

The dynamics of fixed-wing mode are more complex and usually involve both lateral and directional dynamics. The linear state space model for fixed-wing mode can be expressed using the following equations:

Longitudinal dynamic (fixed wing):

$$\begin{bmatrix}\dot{u}\\\dot{w}\\\dot{q}\\\dot{\theta}\end{bmatrix}=\begin{bmatrix}X_u & X_w & 0 & -gcos\theta_0\\Z_u & Z_w & U_0 & -gsin\theta_0\\M_u & M_w & M_q & 0\\0 & 0 & 1 & 0\end{bmatrix}\begin{bmatrix}u\\w\\q\\\theta\end{bmatrix}+\begin{bmatrix}X_{\delta_e}\\Z_{\delta_e}\\M_{\delta_e}\\0\end{bmatrix}[\delta_e] \quad (4)$$

where δ_e is the elevator input and the state variables are defined as $\boldsymbol{x_4}=[u \quad w \quad q \quad \theta]^T$.

Lateral dynamic (fixed wing):

$$\begin{bmatrix}\dot{v}\\\dot{p}\\\dot{r}\\\dot{\phi}\\\dot{\psi}\end{bmatrix}=\begin{bmatrix}Y_V & Y_p & Y_r-U_0 & gcos\theta_0 & 0\\L_v & L_p & L_r & 0 & 0\\N_v & N_p & N_r & 0 & 0\\0 & 1 & \tan\theta_0 & 0 & 0\\0 & 0 & \sec\theta_0 & 0 & 0\end{bmatrix}\begin{bmatrix}v\\p\\r\\\phi\\\psi\end{bmatrix}+\begin{bmatrix}Y_{\delta_a} & Y_{\delta_r}\\L_{\delta_a} & L_{\delta_r}\\N_{\delta_a} & N_{\delta_r}\\0 & 0\\0 & 0\end{bmatrix}\begin{bmatrix}\delta_a\\\delta_r\end{bmatrix} \quad (5)$$

where δ_a and δ_r are the aileron and rudder inputs. The state variables are defined as $\boldsymbol{x_5}=[v \quad p \quad r \quad \phi \quad \psi]^T$.

2.3 The Differential Evolution Algorithm

The Differential Evolution (DE) algorithm is employed as the optimization technique to refine the parameters of the hybrid UAV's dynamic model obtained through system identification. DE is a population-based evolutionary algorithm particularly effective for global optimization problems over continuous search spaces [2]. In this study, DE is used to minimize the error between the predicted outputs of the dynamic model and the actual flight data collected from simulations. An objective function (or cost function) is defined to quantify the mismatch between the model's predicted output and the actual system output as follows:

$$J=\frac{\bar{E}}{2}+\frac{S}{2} \quad (6)$$

where $\bar{E}$ is the average mean square error of n measured outputs, which can be calculated using:

$$\bar{E}=\frac{1}{n}\sum_{i=1}^{n}E_i \quad (7)$$

For N sample size, the mean square error E for a single output is obtained as follows:

$$E=\frac{1}{N}\sum_{i=1}^{N}(\hat{y}(k)-y(k))^2 \quad (8)$$

Additionally, the variation in prediction error can be calculated as the standard deviation of each E_i from $\bar{E}$ using the following relationship:

$$S=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(E_i-\bar{E})^2} \quad (9)$$

The DE process consists of the following key steps:

Initialization:
An initial population of candidate solutions (parameter vectors) is randomly generated within predefined boundaries for each parameter of the dynamic model. This population represents the starting point for the optimization process.

Mutation:
For each individual (target vector) in the current population, a mutant vector is generated. This is typically achieved by selecting two or more distinct individuals (randomly chosen base vectors) from the population,

calculating the weighted difference between two of them, and adding this difference to a third (parent vector) [2]. A common mutation strategy is "DE/rand/1/bin". The mutation operation introduces diversity into the population, allowing for the exploration of new regions in the parameter space.

Crossover (Recombination):
The mutant vector is then combined with the target vector to create a trial vector. A common crossover scheme is binomial crossover, where each parameter of the trial vector is inherited from either the mutant vector or the target vector with a certain probability (crossover constant, CR) [2]. This step facilitates the exchange of promising characteristics between solutions.

Selection:
The trial vector is evaluated against the target vector using a predefined fitness function. In this context, the fitness function quantifies how well the dynamic model with the trial vector's parameters predicts the UAV's behavior compared to the actual data. Typically, the fitness function is designed to minimize the prediction error, such as the mean squared error (MSE). If the trial vector yields a better fitness value (lower error), it replaces the target vector in the next generation; otherwise, the target vector is retained [2]. This selection process ensures that the population evolves towards better solutions over successive generations.

The DE algorithm iteratively applies these steps until a predefined termination criterion is met, such as reaching a maximum number of generations or achieving a satisfactory level of model accuracy. The proposed algorithm can be described by the following algorithm steps:

1. Define the DE parameters: crossover constant ($\boldsymbol{CR}$), mutation constant ($\boldsymbol{F}$), population size ($\boldsymbol{N_p}$), and maximum number of generations ($\boldsymbol{G_{max}}$).
2. Set the iteration $\boldsymbol{k = 0}$. Generate an initial population $\boldsymbol{X_j^0} = \begin{bmatrix}\boldsymbol{X_1} & \boldsymbol{X_2} & \cdots & \boldsymbol{X_{N_p}}\end{bmatrix}^{\boldsymbol{T}}$ using uniform distribution. $\boldsymbol{X}$ represent the unknown parameters of dynamic models.
3. Iteration (for each generation $\boldsymbol{g = 1}$ to $\boldsymbol{G_{max}}$:
   a. Select a random mutant vector $\boldsymbol{X_{r1}^k}$ and $\boldsymbol{X_{r2}^k}$ such that $\boldsymbol{r_1 \neq r_2}$.
   b. Mutation: Generate a mutant vector.

$$\boldsymbol{X_{new,i}^k = X_{best}^k + F\left(X_{r1}^k - X_{r2}^k\right)} \tag{10}$$

   c. Crossover: Apply the crossover operator and calculate the trial vector, $\boldsymbol{U_i^k}$.

$$\boldsymbol{U_i^k} = \begin{cases} \boldsymbol{X_{new,i}^k} & \text{if (rand[0,1]} \leq \boldsymbol{CR} \\ \boldsymbol{X_i^k} & \text{Otherwise} \end{cases} \tag{11}$$

   d. Selection: Determine the trial vector by calculating the objective function for each vector.

$$\boldsymbol{X_i^{k+1}} = \begin{cases} \boldsymbol{U_i^k} & \text{if}\, \boldsymbol{J\left(U_i^k\right) \leq J\left(X_i^k\right)} \\ \boldsymbol{X_i^k} & \text{if}\, \boldsymbol{J\left(U_i^k\right) \geq J\left(X_i^k\right)} \end{cases} \tag{12}$$

4. Termination: The algorithm terminates when a predefined stopping criterion is met, such as reaching the maximum number of generations ($\boldsymbol{G_{max}}$) or achieving a satisfactory fitness value.

The best individual found in the final generation (or the best individual found across all generations) represents the optimized solution to the problem. In the context of hybrid UAV dynamic modeling, this solution would be the set of model parameters that best describe the UAV's response based on the chosen model structure and the collected flight data.

2.4 Model Validation

The model validation is performed using the second data set that is different from the training data set to validate the performance of the resulting model by comparing its predictions to the actual flight data. The validation results are also analyzed based on metrics such as mean squared error (MSE) and the standard deviation ($\boldsymbol{\sigma}$) of the errors. These metrics help to assess the overall accuracy of the model, with MSE reflecting the average magnitude of prediction errors. Additionally, the consistency of the predictions is analyzed by calculating the standard deviation ($\boldsymbol{\sigma}$) of the errors. This metric reveals the variability of prediction errors, helping to assess the model's stability and robustness under varying conditions. These evaluations are essential to determine whether the model can reliably replicate the real-world behavior of the hybrid UAV.

3. Results and Discussion

The differential evolution algorithm discussed in Section 2.3 was used to estimate the unknown parameter set of the quadcopter mode (Eq. (1)–(3)) and fixed-wing UAV state-space model of Eq. (4)–(5). The DE parameters are specified as crossover constant $CR = 0.5$, mutation constant $F = 0.5$, population size $N_p = 20$, and the maximum generation $G_{max} = 250$. The models' performance and accuracy will be tested with various datasets by comparing the predicted outputs to actual flight data. Metrics such as mean square error (MSE) and the standard deviation (σ) of the errors are used to assess the models' fitness and reliability under different operating conditions.

3.1 Training Model Performance

This section reviews the performance of the dynamic model after optimizing its model parameters using the Differential Evolution (DE) algorithm. By optimizing the model parameters derived during the system identification phase, the tuning procedure seeks to reduce the disparities between the observed data and the model's predictions. It is expected that the new model will show noticeably higher accuracy and robustness by utilizing DE's capacity to effectively explore a large range of variables and converge towards an ideal solution. Table 2 and Table 3 show the identified model parameters from the dynamic model by using differential evolution.

Table 2 *Identified parameters for quadcopter mode*

Quadcopter mode	Values
X_u	-0.1365
M_u	0.588068
M_q	30.5018
X_{ele}	35.5789
M_{ele}	0.588068
Y_v	-98.3975
L_v	-8.42724
Y_{ail}	40.5309
L_{ail}	-95.1572
N_r	-98.2604
N_{rud}	-81.2149

Table 3 *Identified parameters for fixed-wing mode*

Fixed-wing mode	Values
X_w	-89.9237
Z_u	-89.7284
Z_w	-99.7284
M_w	-69.9938
Z_{δ_e}	-59.9992
Y_p	-8.24849
Y_r	-8.773
L_p	-91.4208
L_r	-19.9579
N_v	-19.4724
N_p	-19.7894
Y_{δ_r}	-19.981
L_{δ_r}	-19.2013
N_{δ_a}	-18.4544

The results of the training model prediction will be discussed to further study the accuracy of the developed dynamic model. Fig. 3 and Fig. 4 show the model prediction results for both quadcopter mode and fixed wing after implementing the identified parameters in LabVIEW. The model prediction results for the quadcopter response shown in Fig. 3 show a satisfactory fit between the prediction and actual responses for roll rate (p), pitch rate (q), and yaw rate (r) responses. However, the training results show the ineffectiveness of the dynamic model in predicting the forward speed dynamics. This is because the linear state space model used in forward speed prediction is insufficient to identify the forward speed correctly. It is suggested that the nonlinear terms in translational dynamics are used to increase the fidelity of the prediction [20], [21]. The hybrid UAV's fixed-wing mode system identification findings show that the identified dynamic models are capable of predicting all state responses with adequate accuracy. The predictions for roll rate (p) and pitch rate (q) nearly match the observed oscillations, demonstrating how well the model captures rotational dynamics. Additionally, the forward velocity (u), lateral velocity (v), and vertical velocity (w) predictions are close to the measured data, demonstrating the model's ability to capture the translational and velocity dynamics of the UAV. These outcomes confirm that the system identification procedure is a capable method for predicting the response of the hybrid UAV.

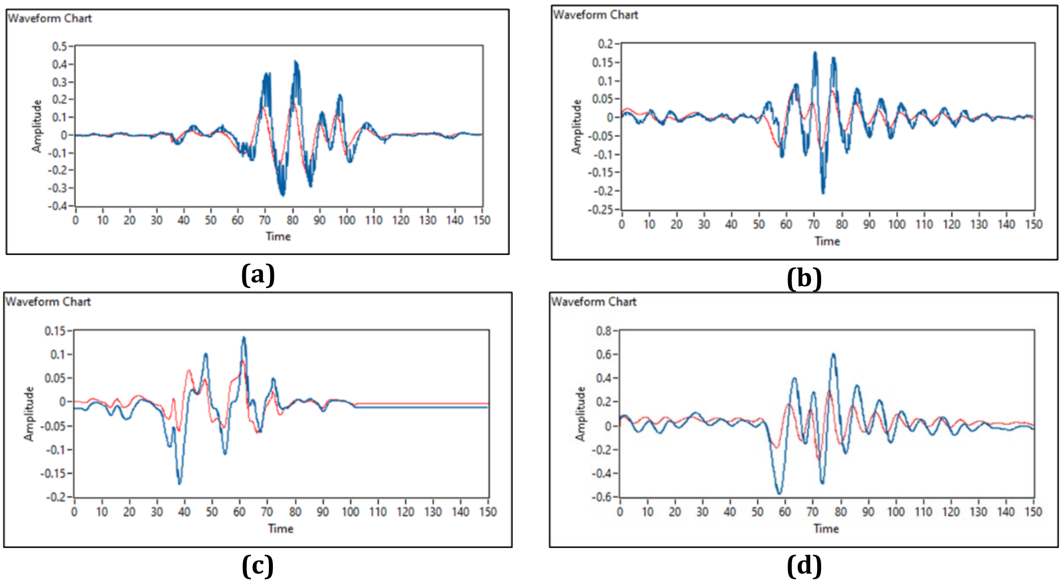


Fig. 3 *Model prediction performance results for quadcopter mode. The red lines represent prediction, and the blue lines represent measurement data. (a) roll rate response; (b) pitch rate response; (c) yaw rate response; and (d) forward speed response*

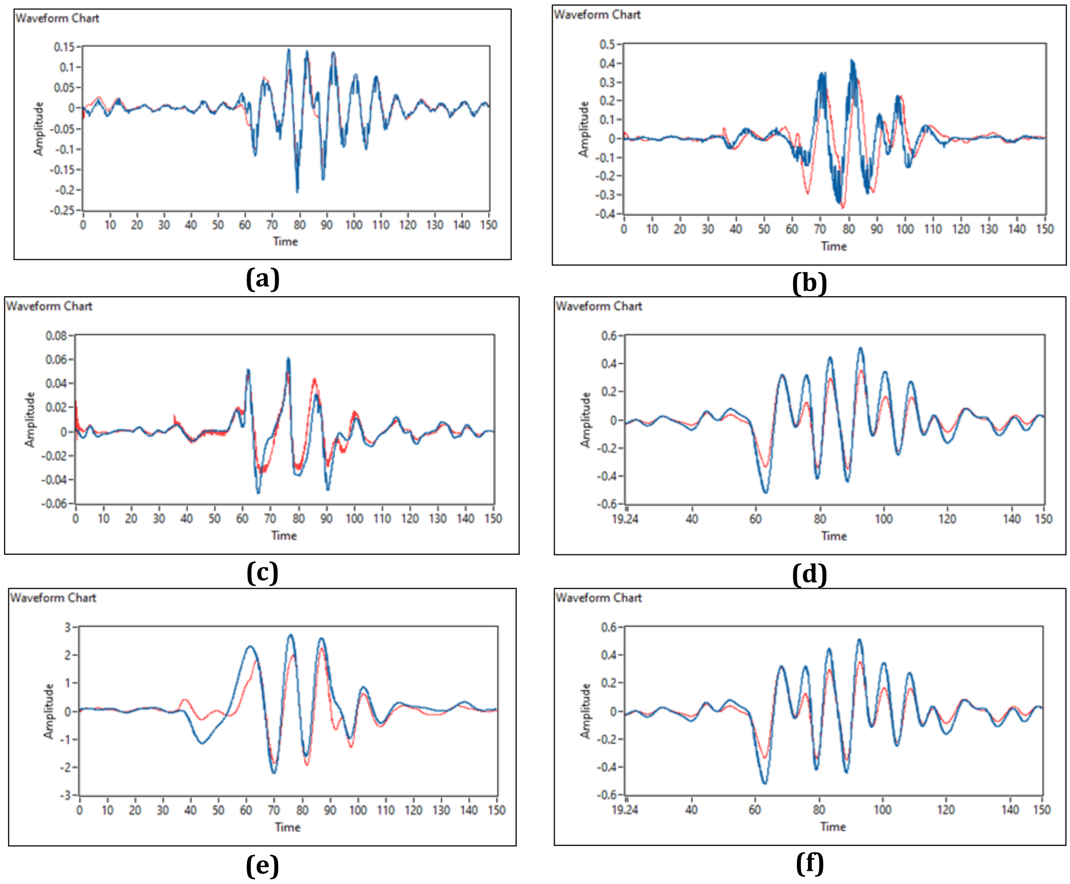


Fig. 4 *Model prediction performance for fixed-wing mode. The red lines represent prediction, and the blue lines represent measurement data. (a) roll rate response; (b) pitch rate response; (c) yaw rate response; (d) forward speed response; (e) lateral speed response; and (f) vertical speed response*

Table 4 and Table 5 show the values of MSE and σ for both quadcopter mode and fixed-wing mode for the hybrid UAV. The evaluation metrics for dynamic models offer details about the UAV's state prediction performance. Statistical metric results from Table 4 show that the roll rate (p), pitch rate (q) and yaw rate (r) models show good predictive accuracy and stability, reflecting reliable performance. The forward speed (u) model demonstrates slight inadequacy in prediction accuracy. Overall, the dynamic models exhibit varying levels of performance, with areas for improvement in specific responses. Table 5 shows the hybrid UAV in fixed-wing mode demonstrating satisfactory prediction accuracy and stability for almost all states. The roll rate (p), pitch rate (q), and yaw rate (r) models exhibit high prediction accuracy, indicating their reliability in capturing the dynamic behavior of the UAV. The forward speed (u) model provides moderate accuracy with stable predictions, highlighting its adequate performance for dynamic predictions. In contrast, the lateral speed (v) and vertical speed (w) models exhibit higher variability, suggesting the need for further refinement to DE parameters to enhance dynamic models' accuracy and reliability. Overall, the identified models effectively represent the UAV's fixed-wing dynamics, providing a satisfactory foundation for control design.

Table 4 *Statistical metrics for quadcopter mode*

Parameters	MSE	σ
p	0.0009368	0.03
q	0.0010124	0.03
r	0.0053114	0.07
u	0.0197192	0.14

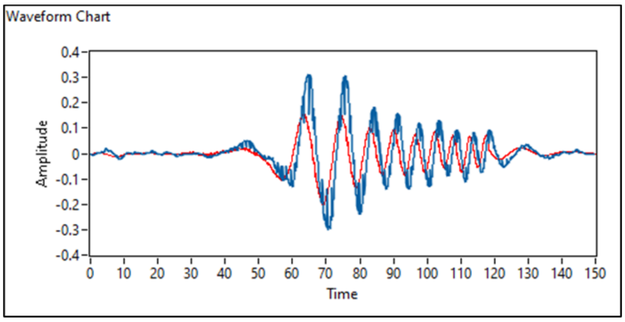
Table 5 *Statistical metrics for fixed-wing mode*

Parameters	MSE	σ
p	0.0000504	0.01
q	0.0089776	0.09
r	0.0007438	0.02
u	0.0046356	0.07
v	0.1862440	0.42
w	0.0183242	0.13

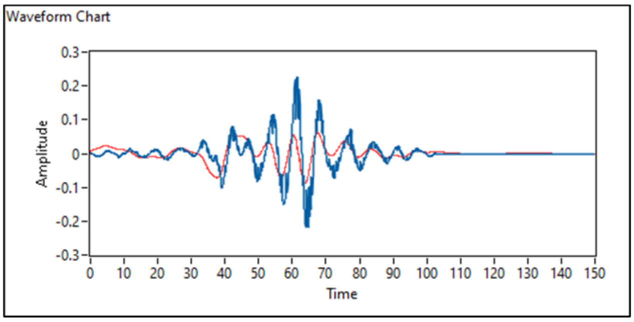
3.2 Model Validation

The model validation process is essential for evaluating the accuracy, robustness, and reliability of the developed system identification model. To test the model's generalization, a new dataset is used for validation, differing from the frequency sweep data utilized during training. The validation focuses on comparing the model's predicted responses with measured data and calculating key statistical metrics, including mean squared error (MSE) and standard deviation of error ($\boldsymbol{\sigma}$).

Figure 5 shows the validation results for the quadcopter model prediction, demonstrating the ability of the model to predict system dynamics with a new dataset. Figure 5(a) depicts roll rate (p) prediction, which predicts the response with acceptable accuracy, but pitch rate (q) prediction achieves adequate accuracy, as illustrated in Figure 5(b). Figure 5(c) shows the inaccurate yaw rate (r) estimates with large errors between the predicted response and the measured data. These results show the ineffectiveness of the dynamic model in identifying yaw dynamics, indicating that Eq. (3) is insufficient to adequately represent yaw dynamics and that a coupled attitude with more stability derivatives, such as in [21], [22], is required to satisfactorily represent the dynamic. Similarly to the model training results, the dynamic model shows an ineffectiveness in identifying the quadcopter's forward speed (u) dynamics. To increase the accuracy of the forward speed (u) prediction, nonlinear terms in translational dynamics can be considered in the DE training to identify the $\boldsymbol{X_u}$ and $\boldsymbol{X_{ele}}$ terms [20], [21].



(a)



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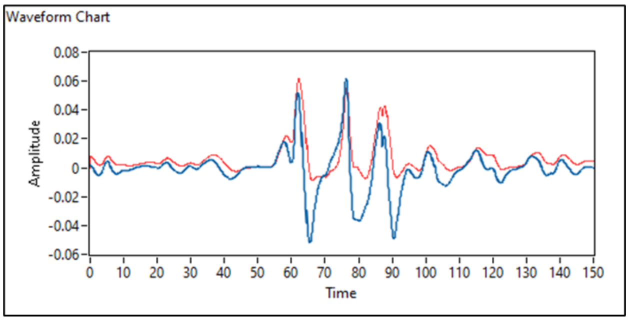
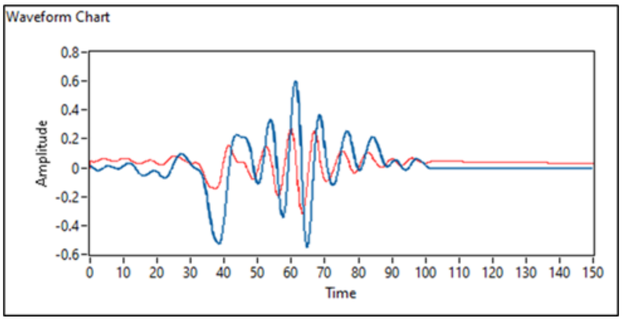


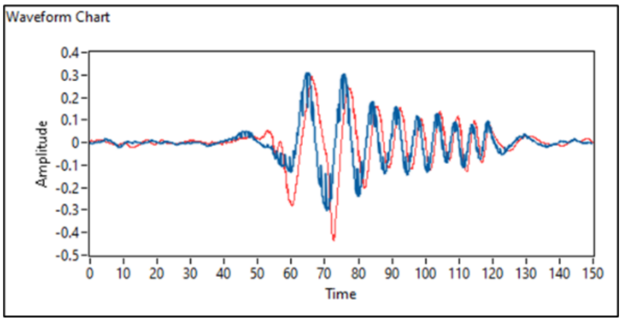
(c)



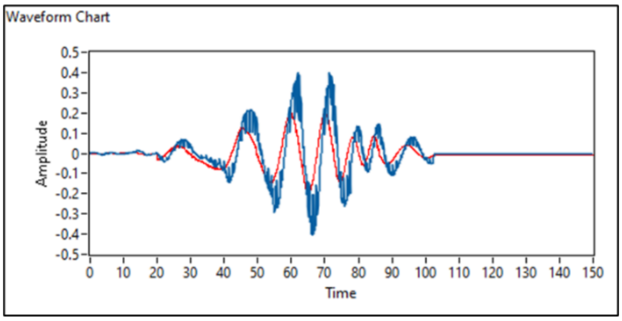
(d)

Fig. 5 *Validation model prediction results for quadcopter mode. The red lines represent prediction, and the blue lines represent measurement data. (a) roll rate response; (b) pitch rate response; (c) yaw rate response; (d) forward speed response*

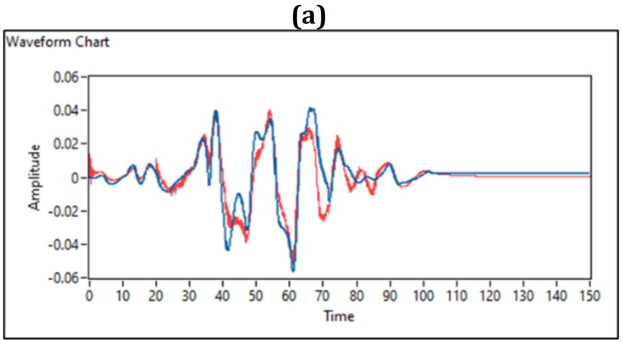
Fig. 6 shows the validation results for the fixed-wing mode, revealing varying levels of prediction accuracy. Fig. 6(a) and Fig. 6(b) show the roll rate ($\boldsymbol{p}$) and pitch rate ($\boldsymbol{q}$) prediction, which aligns closely with the measured data, accurately capturing roll and pitch rate responses. The yaw rate (r) prediction in Fig. 6(c) demonstrates a good fit with the measured data, effectively capturing the yaw dynamic response. Fig. 6(d)-6(f) represent forward (u), lateral (v), and vertical (w) speeds, respectively, where the model predictions exhibit close alignment with the measured data with slight discrepancies. These results validate the robustness and accuracy of the model for fixed-wing mode dynamics and highlight its reliability for further analysis and simulation.



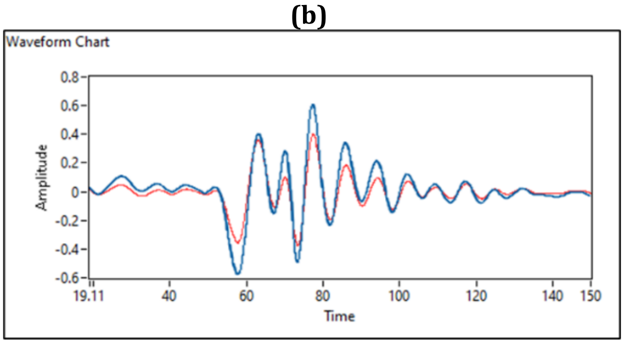
(a)



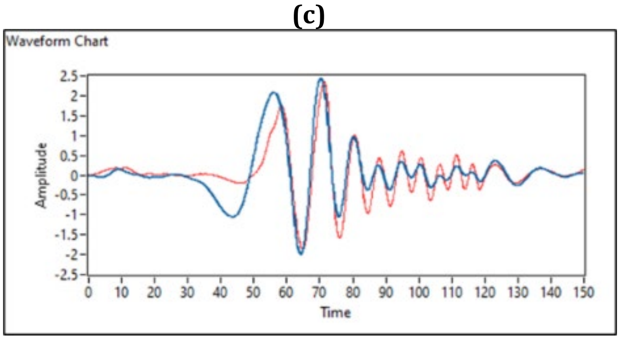
(b)



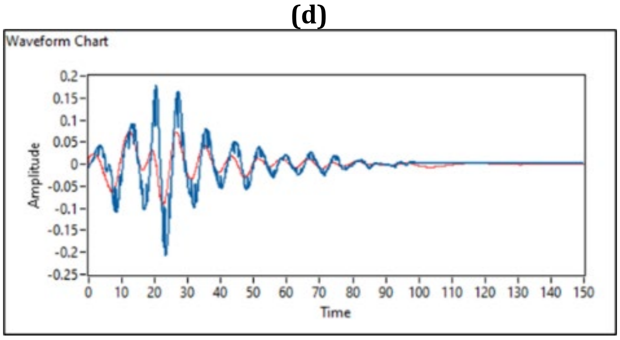
(c)



(d)



(e)



(f)

Fig. 6 *Validation model prediction results for fixed-wing mode. The red lines represent prediction, and the blue lines represent measurement data. (a) roll rate response; (b) pitch rate response; (c) yaw rate response; (d) forward speed response; (e) lateral speed response; and (f) vertical speed response*

Table 6 and Table 7 show the values of statistical metrics calculated from model validation results. Statistical metric results from Table 6 show that the roll rate ($\boldsymbol{p}$) and pitch rate ($\boldsymbol{q}$) show good predictive accuracy and stability, reflecting reliable performance. The yaw rate ($\boldsymbol{r}$) and forward speed ($\boldsymbol{u}$) model demonstrates slight inadequacy in prediction accuracy. Overall, the dynamic models exhibit varying levels of performance, with areas for improvement in specific responses. Statistical metric results from Table 7 show that the roll rate ($\boldsymbol{p}$), pitch rate ($\boldsymbol{q}$) and yaw rate ($\boldsymbol{r}$) models for fixed-wing mode show good predictive accuracy and low variability, reflecting reliable performance. The lateral speed ($\boldsymbol{v}$) model demonstrates slight inadequacy in prediction accuracy.

Table 6 *Statistical metrics for quadcopter*

Parameters	MSE	σ
p	0.0005214	0.03
q	0.0045161	0.05
r	0.0248625	0.05
u	0.0132254	0.12

Table 7 *Statistical metrics for fixed-wing*

Parameters	MSE	σ
p	0.0089776	0.09
q	0.0007438	0.02
r	0.0000504	0.01
u	0.0046356	0.07
v	0.1862440	0.42
w	0.0183242	0.13

The performance and testing of the model created were carefully examined to see how well it can predict the system's changing behavior in different operating situations. The fixed-wing mode demonstrated robust performance in both training and testing processes, with strong predictive accuracy for both transient and steady-state behaviors and reliable representation of system dynamics. In contrast, the quadcopter mode showed comparatively lower performance, particularly in capturing dynamic transitions and steady-state stability. Statistical metrics, including standard deviation (σ) and mean squared error (MSE), confirmed the robustness of the fixed-wing model, making it suitable for future analytical and simulation tasks. However, improvements are necessary for the quadcopter mode to enhance its predictive accuracy and reliability. These improvements include adjusting the Differential Evolution (DE) algorithm settings, incorporating additional parameters to better capture quadcopter dynamics, and restructuring the model architecture for better representation of the system. Overall, while the fixed-wing mode model is well-validated and robust, addressing the identified limitations in the quadcopter mode will further enhance the overall model performance and dependability.

4. Conclusion

This research successfully developed dynamic models for a small hybrid Unmanned Aerial Vehicle (UAV) using a system identification approach optimized by the Differential Evolution (DE) algorithm, incorporating processes like initialization, mutation, crossover, and selection. The training and validation data was gathered using frequency-swept excitation techniques from simulations and the models were assessed using statistical metrics like mean squared error (MSE) and standard deviation of error (σ). These results indicated the models could effectively predict the UAV's flight dynamics, capturing the general behavior of the quadcopter and fixed-wing modes for responses such as forward speed, lateral speed, vertical speed, roll rate, pitch rate, and yaw rate. Several areas for future improvement are recommended to further improve the models and contribute to the advancement of hybrid UAV modeling and control systems. One significant recommendation is to conduct real-world flight tests to validate the models under actual operating conditions, as these tests provide detailed and realistic data on UAV performance in its operational environment, despite potential costs, time, and risks. Extending the models to include nonlinear dynamics is crucial for greater accuracy, particularly in complex flight scenarios, given that helicopter systems, including quadrotors, have complex dynamics and nonlinearities. Additionally, collecting data across a wider range of input signals, environmental conditions, and flight regimes is suggested to improve model training and validation. Exploring alternative optimization algorithms, such as genetic algorithms or particle swarm optimization (PSO), is another area for future work to compare their performance with differential evolution. PSO methods have been applied to system identification for small unmanned aerial vehicles. These improvements will further strengthen the models and contribute to the advancement of hybrid UAV modeling and control systems.

Acknowledgement

This research was supported by Universiti Tun Hussein Onn Malaysia (UTHM) through Tier 1 (Vot. Q898) research grant.

Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm their contribution to the paper as follows: ***study conception and design:*** *Abdul Malek Akalil and Syariful Syafiq Shamsudin;* ***data collection:*** *Mohamad Fahmi Pairan and Abdul Malek Akalil*; ***analysis and interpretation of results:*** *Mohamad Fahmi Pairan and Abdul Malek Akalil;* ***draft manuscript preparation:*** *Abdul Malek Akalil and Syariful Syafiq Shamsudin. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] T. Jiang, J. Li, and K. Huang, "Longitudinal parameter identification of a small unmanned aerial vehicle based on modified particle swarm optimization," *Chinese Journal of Aeronautics*, vol. 28, no. 3, pp. 865–873, Jun. 2015, doi: 10.1016/j.cja.2015.04.005.

[2] I. B. Tijani, R. Akmeliawati, A. Legowo, A. Budiyono, and A. G. Abdul Muthalif, "Hybrid DE-PEM algorithm for identification of UAV helicopter," *Aircraft Engineering and Aerospace Technology*, vol. 86, no. 5, pp. 385–405, Aug. 2014, doi: 10.1108/AEAT-11-2012-0226.

[3] G. Hoffmann, H. Huang, S. Waslander, and C. Tomlin, "Quadrotor Helicopter Flight Dynamics and Control: Theory and Experiment," in *AIAA Guidance, Navigation and Control Conference and Exhibit*, Reston, Virginia: American Institute of Aeronautics and Astronautics, Aug. 2007. doi: 10.2514/6.2007-6461.

[4] A. Budiyono, T. Sudiyanto, and H. Lesmana, "First Principle Approach to Modeling of Small Scale Helicopter," Institut Teknologi Bandung, 2007. Accessed: Jun. 16, 2024. [Online]. Available: https://www.researchgate.net/publication/220482076_First_Principle_Approach_to_Modeling_of_Small_Scale_Helicopter

[5] "System Identification Overview," MathWorks. Accessed: Jun. 04, 2024. [Online]. Available: https://www.mathworks.com/help/ident/gs/about-system-identification.html

[6] I. Z. Mat Darus and M. O. Tokhi, "Parametric and Non-Parametric Identification of a Two-Dimensional Flexible Structure," *Journal of Low Frequency Noise, Vibration, and Active Control*, pp. 119–143, 2005.

[7] G. Nanos, "Differences Between a Parametric and Non-parametric Model," Baeldung.

[8] M. Gevers and L. Ljung, "Optimal experiment designs with respect to the intended model application," *Automatica*, vol. 22, no. 5, pp. 543–554, Sep. 1986, doi: 10.1016/0005-1098(86)90064-6.

[9] Skill-Lync, "An Overview of The Differences between Time Domain and Frequency Domain," Skill-Lync. Accessed: Jun. 04, 2024. [Online]. Available: https://skill-lync.com/blogs/technical-blogs/electrical-an-overview-of-the-differences-between-time-domain-and-frequency-domain

[10] I. Chiha, J. Ghabi, and N. Liouane, "Tuning PID controller with multi-objective differential evolution," in *2012 5th International Symposium on Communications, Control and Signal Processing*, IEEE, May 2012, pp. 1–4. doi: 10.1109/ISCCSP.2012.6217801.

[11] G. Li, Q. Jia, and J. Shi, "The Identification of Unmanned Helicopter Based on Improved Evolutionary Strategy," in *2009 Second International Conference on Intelligent Computation Technology and Automation*, IEEE, 2009, pp. 205–208. doi: 10.1109/ICICTA.2009.58.

[12] M. F. Pairan, S. S. Shamsudin, and M. F. Yaakub, "Autotuning PID Controllers for Quadplane Hybrid UAV using Differential Evolution Algorithm," *Journal of Aeronautics, Astronautics and Aviation*, vol. 56, no. 1S, pp. 341–356, 2024, doi: 10.6125/JoAAA.202403_56(1S).23.

[13] S. H. Yi, S. S. Shamsudin, and M. F. Pairan, "Flight Control System Design for a Rotorcraft-Based Unmanned Aerial System using Pole Placement and LQR-Based PID Tuning Techniques," *Journal of Aeronautics, Astronautics and Aviation*, vol. 56, no. 3, pp. 615–636, 2024, doi: 10.6125/JoAAA.202407_56(3).01.

[14] I. Mohammed Shukor, S. S. Shamsudin, and M. F. Pairan, "Flight Controller Design for a Helicopter-Based Unmanned Aerial Vehicle (UAV) Using Differential Evolution-Based PID Tuning," *Progress in Aerospace and Aviation Technology*, vol. 4, no. 2, pp. 36–50, 2024, accessed Dec. 27, 2024. [Online]. Available: https://publisher.uthm.edu.my/ojs/index.php/paat/article/view/16735

[15] A. S. Jemsa, S. S. Shamsudin, and M. F. Pairan, "Flight Control System Design and Dynamic Simulation for DJI F450 Quadcopter UAV using Pole Placement Tuning Method," *Progress in Aerospace and Aviation Technology*, vol. 4, no. 2, pp. 17–35, 2024, accessed Dec. 27, 2024. [Online]. Available: https://publisher.uthm.edu.my/ojs/index.php/paat/article/view/16673

[16] M. B. Tischler and R. K. Remple, *Aircraft and Rotorcraft System Identification, Second Edition*. 2012. doi: 10.2514/4.868207.

[17] M.-H. Do, C.-E. Lin, and Y.-C. Lai, "Validation of the Flight Dynamics Engine of the X-Plane Simulator in Comparison with the Real Flight Data of the Quadrotor UAV Using CIFER," *Drones*, vol. 7, no. 9, p. 548, Aug. 2023, doi: 10.3390/drones7090548.

[18] A. Bittar, H. V. Figuereido, P. A. Guimaraes, and A. C. Mendes, "Guidance software-in-the-loop simulation using X-plane and Simulink for UAVs," in *2014 International Conference on Unmanned Aircraft Systems (ICUAS)*, IEEE, 2014, pp. 993–1002.

[19] W. Wei, M. B. Tischler, N. Schwartz, and K. Cohen, "System Identification and Flight Control of an Unmanned Quadrotor," in *Advanced UAV Aerodynamics, Flight Stability and Control*, Wiley, 2017, pp. 695–727. doi: 10.1002/9781118928691.ch21.

[20] C. Liu and W. Chen, "Dynamics Modelling and System Identification of Small Unmanned Helicopters," in *Advanced UAV Aerodynamics, Flight Stability and Control*, Wiley, 2017, pp. 255–282. doi: 10.1002/9781118928691.ch7.

[21] C. Liu, "Advanced control for miniature helicopters: modelling, design, and flight test," Doctoral Thesis, Loughborough University, 2011. Accessed: Jan. 01, 2023. [Online]. Available: https://repository.lboro.ac.uk/articles/thesis/Advanced_control_for_miniature_helicopters_modelling_design_and_flight_test/9219728

[22] M. Chipofya, D. J. Lee, and K. T. Chong, "Trajectory Tracking and Stabilization of a Quadrotor Using Model Predictive Control of Laguerre Functions," *Abstract and Applied Analysis*, vol. 2015, pp. 1–11, 2015, doi: 10.1155/2015/916864.