drones

Article

Hybrid DNN-Based Flight Power Estimation Framework for Unmanned Aerial Vehicles

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Abstract: Unmanned Aerial Vehicles (UAVs) have been widely used in logistics and communication, though they were initially used for military purposes. However, because the motor must always be rotated, the flight range of an UAV is limited, which, in turn, restricts the scope of UAV applications. Of course, if UAV power consumption is predicted using AI, it is possible to effectively plan UAV operations by deriving optimal energy-efficient flight paths during the simulation phase. However, when using deep neural networks (DNNs) to build a UAV power consumption model, it is difficult to make accurate inferences based solely on flight velocity data. For precise predictions, random vibration acceleration data, as a result of thrust and resistance, are also required. Unfortunately, such information cannot be obtained during the simulation phase and can only be acquired through the actual flight environment. In this paper, we propose the first hybrid DNN-based power model that combines a DNN-based power consumption model and a data-driven random vibration acceleration model that derives UAV random vibration acceleration information based on flight velocity and environment. The proposed modeling framework was evaluated with flight experiments, demonstrating a 6.12% root mean squared percentage error (RMSPE), which is 39.45% more accurate when compared with a conventional DNN-only power model. In addition, we performed case studies to show that it is possible to find energy-efficient flight paths.

Keywords: unmanned aerial vehicles; deep neural network; power consumption; empirical method

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1. Introduction

Unmanned Aerial Vehicles (UAVs) are increasingly being utilized across various sectors, extending beyond military applications to include use in logistics, communication, and transportation. The global UAV market is projected to reach 1445 billion dollars by 2034, nearly 24 times in size since 2024 [1]. The rapid advancements in unmanned flight technologies, such as automatic altitude maintenance and autonomous navigation, are positioning UAVs as a vital component of modern transportation networks alongside traditional air, sea, and land transport. This shift is particularly evident in urban delivery and logistics, where major companies like Amazon and UPS are transitioning to UAV-based systems to enhance efficiency and to meet growing demand. Originally, UAVs were designed to access dangerous areas that are challenging for humans to reach like war fields or fire sites. In these days, thanks to advancements in high-power battery technology and other cutting-edge fields like aviation, communications, and sensors, the scope of UAV applications has been extended to commercial sectors such as goods delivery and surveillance. For example, UAVs are well suited for urban goods delivery due to their lower initial capital investment and maintenance costs when compared to traditional aviation. In addition, they do not require a runway for taking off [2].

Typical UAVs use high-power batteries to constantly obtain thrust while in the air. At the same time, a UAV's flight range is limited by its battery capacity. The ideal batteries needed for optimal UAV performance have the combination of high power and high energy, particularly in terms of discharge current, energy density, lifespan, and charge/discharge efficiency [3]. This limitation makes it challenging for UAVs to perform multiple activities simultaneously. To address the restricted flight range, fuel cell batteries have been proposed as an alternative. For instance, a company introduced a fuel cell module delivering a continuous power output of 800 W at a weight of 930 g [4]. With this module, the DJI M600 PRO (DJI, Shenzhen, China) can achieve a flight time of over 80 min, nearly four times longer than when using a typical lithium-ion polymer battery, with a 3 kg payload. However, the use of fuel cells limits flight speed and acceleration due to safety concerns, potentially impeding evasive maneuvers in strong winds or crash-risk situations.

One of the most effective strategies for conserving energy is to develop an optimal flight profile—a plan that specifies both the route and velocity over time to minimize energy consumption. Predictions of accurate power consumption for various flight profiles are crucial before conducting the actual flight. Figure 1 shows the typical decision process for the UAV flight operation, such as surveillance and parcel delivery. First, the UAV specification is defined for the flight operation, such as maximum payload W_{max}, maximum flight velocity V_{max}, etc. Then, flight constraints for the operation are defined, such as the flight deadline and scanning locations. The information is used to synthesize the flight profile $L(t)$ to perform the mission. The profile includes the positions (x, y, z) of the UAV over time. The power profile $P(t)$ must be estimated by $L(t)$ to check the profile is feasible under the given battery. If the power capacity or energy capacity of the battery is not enough, one should choose another $L(t)$ or, in the worst case, another type of UAV should be used. As shown in below case, the need for estimating the power consumption of UAVs is inevitable.

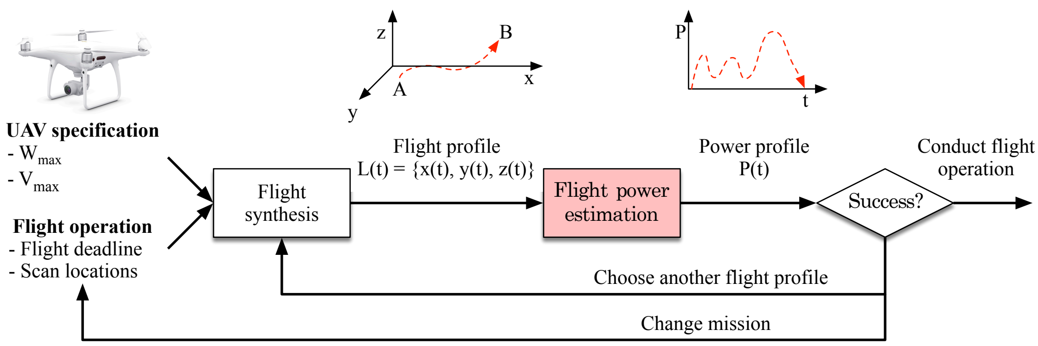

Figure 1. UAV flight profile decision process.

However, predicting the power consumption of UAVs is more complex than that of ground vehicles. Unlike vehicles, UAVs must continuously expend additional energy to maintain altitude and stabilize against gravity and posture control. This extra energy demand is substantial and cannot be overlooked, further complicating the power consumption modeling process. One promising approach to estimating UAV power consumption is to approximate it on a per-distance basis using experimental flight data. However, this method faces significant limitations. The energy requirements of UAVs differ markedly across various flight modes (vertical, horizontal, and mixed), resulting in substantial variability in power consumption. This variability poses a serious challenge in achieving the high level of accuracy needed for reliable flight range estimation.

Deep neural networks (DNNs) are frequently used to construct complex models, such as ones that estimate flight power consumption. These models are generally trained using data that correlate power consumption with UAV movements. However, it remains challenging to accurately predict power consumption for a synthesized flight profile. A precise DNN-based power model typically requires accounting for both the UAV's velocity and acceleration, as the acceleration has a significant impact on power consumption. Unfortunately, $L(t)$ usually provides only velocity information, leaving out crucial random vibration acceleration data.

As the mass of a drone increases, the amplitude of random vibration acceleration tends to decrease, aligning with principles of general dynamics, such as the harmonic oscillator model. Consequently, acceleration-related factors, including random vibrations, are less significant for larger drones. This means that power modeling is much easier for larger drones. However, this relationship does not apply to smaller drones, where vibrations remain a crucial factor to consider [5]. This challenge is compounded by the fact that random vibration acceleration cannot be accurately derived by simply differentiating velocity. Figure 2 demonstrates this disparity, showing the difference between the horizontal velocity and acceleration data recorded by the UAV's inertial measurement unit (IMU) over 30 s. Notably, random vibration acceleration is observed even during hovering, where there is no horizontal movement, and it still contributes to power consumption. Additionally, a significant acceleration spike is detected at the 7-s mark when the UAV changes its velocity monotonically; this is attributable to factors such as posture control rather than just changes in speed. These observations indicate that random vibration acceleration cannot be accurately inferred from velocity data alone. Instead, it is more feasible to derive random vibration acceleration by analyzing the movement characteristics of the UAV, which is obtained through experimental data.

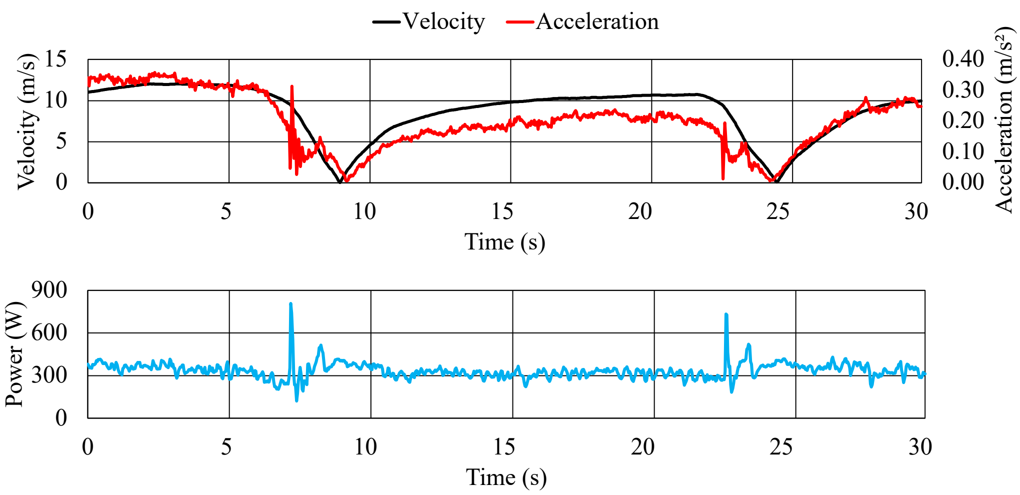

Figure 2. Comparison of velocity, acceleration and corresponding power consumpiton.

In this paper, we propose a hybrid DNN-based UAV flight power estimation framework for the UAV $L(t)$ decision process, as shown in Figure 1. First, we conducted UAV flight experiments to analyze the power consumption across different flight patterns. To gather comprehensive experimental data, we performed both simple, constant flight patterns and complex, mixed patterns involving combinations of vertical and horizontal flights. Second, we propose an acceleration model that includes random vibration and posture control during the flight. A typical accurate power model requires acceleration, as well as velocity, information. However, there is a meaningful difference between simple changes in velocity and all other kinds of acceleration information, including random vibration. Our proposed model incorporates the impact of posture control, which generates hidden acceleration. Third, we developed a power consumption model using a DNN trained on the collected experimental data. This model includes exact acceleration as an input in the DNN training process, which enhances the model's accuracy in reflecting the effects of gravity and posture control. We validated its accuracy against both standard power consumption models and the measured experimental data. Finally, we validated the overall accuracy and applicability of the proposed UAV flight power estimation framework, achieving an RMSPE of just 6.12%, which is 39.45% more accurate compared with the DNN-only power model. Additionally, a case study demonstrated the framework's capability to determine the UAV's optimal energy-efficient route.

Section 2 summarizes related work on power consumption models of UAVs and their limitations. Section 3 introduces a newly proposed UAV flight power estimation framework, which includes the DNN-based power consumption model and data-driven acceleration model. Section 4 shows the experimental results of an UAV flight for the purposes of modeling, data analysis, and model validation. Case studies are used to show the suitability of the proposed framework in Section 5. The conclusions of this paper are summarized in Section 6.

2. Flight Power Estimation

2.1. Related Work

One of the primary concerns for UAVs is their limited flight range. One possible solution is to increase the size of the battery pack. However, this approach introduces a trade off as the increased battery weight leads to higher power consumption during flight, which is more significant compared to terrestrial vehicles. Furthermore, improvements in hardware energy efficiency have largely plateaued, with electric motor efficiencies already exceeding 90%. As a result, researchers are focusing on optimizing UAV operations to improve energy efficiency. This includes strategies such as identifying energy-efficient flight routes, velocities, and altitudes. If a power consumption model can be developed, it would allow for the prediction of energy usage through simulations, enabling the derivation of optimal flight routes in offline scenarios.

Various mathematical methods have been employed to predict the power consumption of UAVs. Mathematical modeling is typically used to calculate the dynamics of quadrotors and the motor energy consumption required to generate thrust [6,7]. Through such models, the relationships between flight velocity and motor angular speed are established, as well as the effects of horizontal and vertical flight velocities on power consumption. These relationships provide theoretical insights for determining optimal flight velocity. However, accounting for external factors, such as wind speed at varying altitudes, which influences the energy consumption during hovering, remains a significant challenge. Some researchers have adopted empirical approaches to derive power consumption models [8]. By analyzing UAV flight monitoring data, they examined the effects of key factors such as payload, velocity, and wind on energy consumption. These parameters were then summarized into a linear model. Another study focused on predicting power consumption using a regression-based approach [9]. That study collected data using GPS and categorized the cases into four distinct movement types: hovering, horizontal movement, vertical upward movement, and vertical downward movement. While this approach provides valuable insights, it does not account for combined horizontal and vertical movements. To address this limitation, the present study aims to develop a comprehensive power model that can be applied to all movement scenarios, including combined movements.

There have also been numerous efforts to enhance the accuracy of power consumption models using machine learning techniques. For instance, some researchers have proposed a DNN-based UAV power consumption model built upon extensive flight experimental data [10]. By collecting a wide range of flight information, including GPS data, wind force, and accelerations, they developed a reliable power consumption model. In another study, the authors actively utilized three-axis acceleration data to design an AI network aimed at accurately estimating UAV power consumption [11,12]. Additionally, research has been conducted to apply machine learning techniques using roll, pitch, yaw, and three-axis speed as input features instead of acceleration [13].

However, effectively utilizing DNN-based power models for flight simulation poses challenges. In a simulation environment, as shown in Figure 1, $L(t)$ typically provides only position and velocity information over time, lacking detailed acceleration data such as the vibrations caused by UAV posture corrections. This is because detailed information like UAV vibration by the wind is not typically considered. Due to the lack of acceleration data, it is not possible to effectively utilize an accurate UAV power model even when the model itself is highly accurate. Thus, it is necessary to generate reliable acceleration data from $L(t)$ to improve the accuracy of flight simulations. This paper proposes a hybrid approach that utilizes two models: one that derives acceleration solely from velocity as input data, and a power model that uses both velocity and the derived acceleration as inputs.

2.2. Flight Power Estimation Methods

Figure 3 shows the typical power estimation framework. First, the flight profile as time-based location data $L(t)$ is given in the simulation stage, and the velocity and acceleration information are derived through differentiation. At this point, the power consumption at a given time is derived using the provided power model. Therefore, it is the most important to construct an accurate power model for the purpose of obtaining a precise $P(t)$. While there were various processes conducted for constructing a power model in the previous work, this paper introduces two commonly used approaches: a polynomial model using linear regression, which is one of the most widely adopted methods; and a network model using DNNs, which has recently gained significant traction.

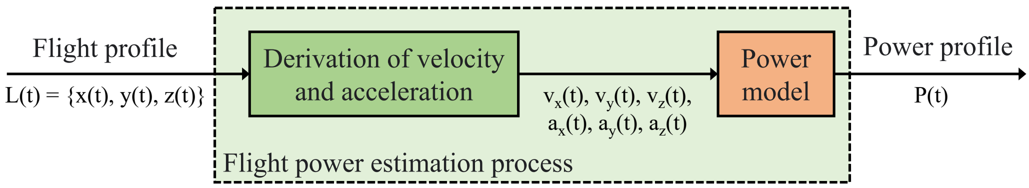

Figure 3. Typical power estimation framework.

2.2.1. Polynomial Power Model

The polynomial model has been widely employed in modeling various systems due to its simplicity. Typically, a polynomial model can be applied if a correlation between two variables (such as, for example, flight acceleration and power consumption) is observed during the data analysis process. The coefficients of the below polynomial model are derived using the linear regression algorithm.

$$Y = a_0 + a_1 X + a_2 X^2 + a_3 X^3 + \ldots a_i X^i. \quad (1)$$

In this UAV power estimation process, as we confirm in Figure 2, there is a correlation between horizontal acceleration and power consumption. Therefore, a polynomial model for power consumption was constructed using horizontal acceleration as the input $X = a_h$.

To derive the horizontal acceleration, which is the input for the power model, the following equation was utilized:

$$
\begin{aligned}
v_x(n) &= \frac{x(n) - x(n-1)}{T}, \quad v_y(n) = \frac{y(n) - y(n-1)}{T}, \\
a_x(n) &= \frac{v_x(n) - v_x(n-1)}{T}, \quad a_y(n) = \frac{v_y(n) - v_y(n-1)}{T}, \\
a_h(n) &= \sqrt{a_x(n)^2 + a_y(n)^2}.
\end{aligned} \tag{2}
$$

where n is the sample index, and T is the sampling period of the collected data.

2.2.2. DNN-Only Power Model

To develop a power prediction model that simultaneously accounts for both vertical and horizontal flight, we should consider various factors, including the UAV's mechanical energy, operational principles, and battery characteristics. However, creating a comprehensive power estimation model by incorporating all these factors results in a highly complex function and requires an extensive amount of data, which presents certain limitations.

Machine learning is one approach that overcomes the limitations of traditional modeling methods by providing a simpler yet highly accurate model using limited data. By training the computer to recognize the relationship between dependent and independent variables, machine learning can generate a model that predicts independent variables.

Among machine learning methods, DNN is a data-driven, black box-type modeling technique that makes predictions and classifications based on training data [14,15]. Figure 4 shows the typical structure of DNN to infer $P(t)$ with $v_x(t)$, $v_y(t)$, and $v_z(t)$, where the velocities of a UAV are derived from differentiation like in (2). Several hidden layers are situated between the input layer (representing UAV velocity) and the output layer (representing UAV power consumption). As the number of hidden layers increases, the model can capture more complex relationships within the data, enabling more accurate modeling with fewer parameters when compared to traditional data estimation methods. However, as the number of hidden layers increases, the time required for training also grows. Moreover, using an excessively large number of hidden layers can lead to reduced accuracy as the model may become overly complex and prone to overfitting.

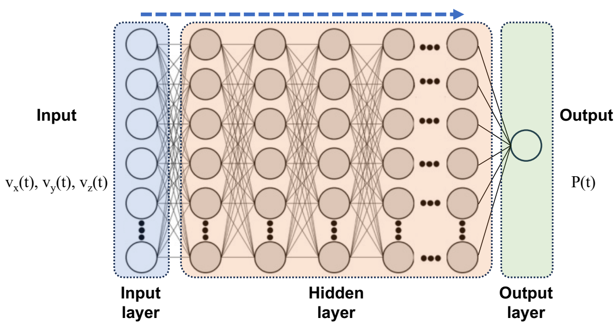

Figure 4. DNN structure. The output is inferred through weighted calculations from left to right direction.

3. Hybrid DNN-Based Flight Power Estimation

Figure 5 illustrates the proposed hybrid DNN-based power modeling framework that includes the flight experiment process in the yellow dashed box and the power estimation process in the green dashed box, respectively. The flight power estimation process is also applied to a red box in Figure 1. The collection and analysis of flight data are essential for developing the data-driven acceleration model and the DNN-based power model.

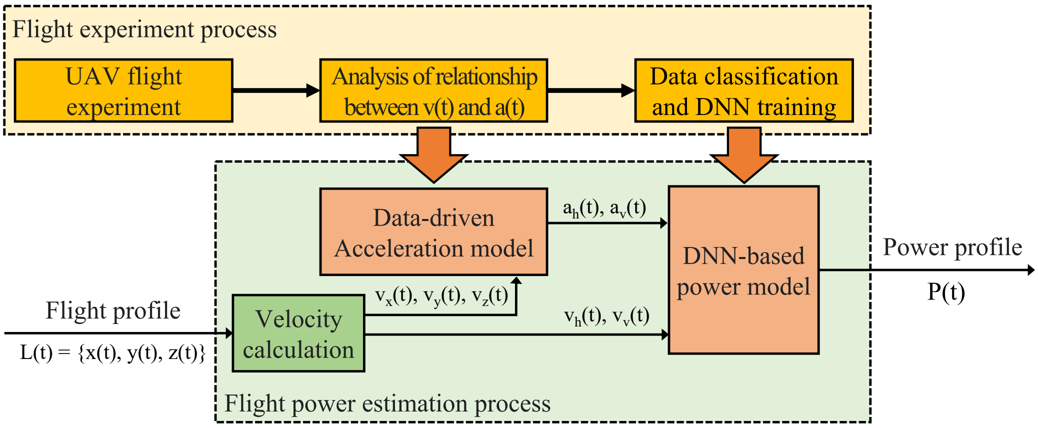

Figure 5. The proposed flight power estimation framework.

The UAV flight experimental data are analyzed to figure out the relationship between velocity and acceleration. The acceleration characteristic was used to construct the data-driven acceleration model that is discussed in Section 3.3. Meanwhile, flight information, including velocity, acceleration, and related power data, was employed to train the DNN-based power model, as described in Section 3.2. When provided with $L(t)$, which consists of UAV position data over time $x(t), y(t)$, and $z(t)$—i.e., the output from the flight synthesis that is shown in Figure 1—then this information is used to derive the velocity profiles along the three axes of $v_x(t), v_y(t)$, and $v_z(t)$. They are then used to compute the accelerations in the horizontal and vertical directions, denoted as $a_h(t)$ and $a_v(t)$, by the data-driven acceleration model. This acceleration information, along with $v_x(t), v_y(t)$, and $v_z(t)$, is fed into the DNN-based power model. The power model then outputs $P(t)$ corresponding to the given $L(t)$.

3.1. Data Collection

First, a suitable UAV was selected for the flight operation. Then, extensive flight data were collected through various types of flight experiments. Typically, a UAV incorporates a range of core technologies to ensure successful flight operations over extended periods. A key component is the flight controller, which ensures safe flight by maintaining the UAV's posture, thus preventing it from losing stability due to external forces such as wind. The flight controller manages three-axis movements—roll, pitch, and yaw—which are essential for hovering, moving forward and backward, and turning left or right.

Then, accurate sensing devices are required to monitor UAV movements and analyze the corresponding energy consumption effectively. GPS is widely used to track an object's position over time. Since GPS data can provide the real-time position, velocity, acceleration, and corresponding power consumption of a UAV, it is highly effective for the power modeling proposed in this paper. However, there are several limitations when using GPS data. A key limitation of GPS is that it does not directly measure velocity and acceleration. Instead, it calculates these values based on position data, making it less effective at accurately capturing acceleration changes caused by factors like wind or attitude control adjustments. Additionally, its low sensing frequency poses challenges for precise modeling. For instance, a sensor that measures motor voltage and current captures 30 points per second while GPS provides only 5 points per second, thus making it difficult to accurately determine the UAV's velocity and acceleration.

An IMU, comprising accelerometers and gyroscopes, directly measures a UAV's velocity, acceleration, and rotational rates. Unlike GPS, which calculates speed and acceleration indirectly from positional data, the IMU's high sampling frequency enables it to capture detailed flight dynamics, including rapid maneuvers and subtle adjustments. This capability is crucial for analyzing the power consumption related to flight control activities, such as maintaining stability and orientation. Operating independently of external signals, the IMU ensures uninterrupted data collection, even in environments where GPS may be unreliable. Moreover, its power consumption is minimal when compared to the UAV's total energy usage, making it an efficient choice for continuous monitoring. For these reasons, this study utilized IMU data to develop the proposed flight power estimation framework.

The proposed model is designed to be highly adaptable as it can inherently account for environmental factors such as wind and temperature when trained with sufficient data. By collecting speed, acceleration, and power data under diverse environmental conditions within a specific region, the DNN can effectively learn the influence of these factors, or they can be incorporated into linear regression or linear equations. The weights of the DNN or the slope and intercept of the linear equations naturally reflect the effects of environmental variables, thus enabling the model to perform robustly under varying conditions.

Additionally, the model's flexibility allows it to be tailored to specific regions, enhancing its accuracy by addressing regional environmental characteristics rather than relying on a universal model. This adaptability minimizes the need for a direct consideration of environmental factors as the data-driven approach ensures that these variables are implicitly included in the model's predictions. This approach highlights the model's strength in handling complex environmental influences, while also providing a clear path for further refinement through region-specific modeling if required.

The collected flight data were thoroughly analyzed to identify and address any erroneous monitoring results, ensuring the accuracy and reliability of the dataset. This process also ensured that the dataset provided a uniform representation of a diverse range of flight movements. After validation, the data were classified and prepared for machine learning-based modeling, forming the foundation for the proposed framework.

3.2. DNN-Based Power Model

Figure 6 illustrates the structure of the DNN-based power model. This process begins with obtaining flight information: $v_h(t)$, $v_v(t)$, $a_h(t)$, and $a_v(t)$. These are used as independent variables for training the DNN. The corresponding $P(t)$ at each UAV motor is set as the dependent variable. Next, the neural network environment variables are configured to enable efficient deep learning. These variables determine how to allocate weights, measure errors, and choose the optimization function. The number of hidden layers is also specified at this stage. Once the independent variables and environment settings are in place, the neural network is run to generate a prediction of $\widehat{P(t)}$. This predicted output is then compared with the measured $P(t)$. The environment variables are updated based on the difference between the predicted and measured data. The propagation of the neural network is repeated, and if the difference falls below a specified threshold, the training process is terminated.

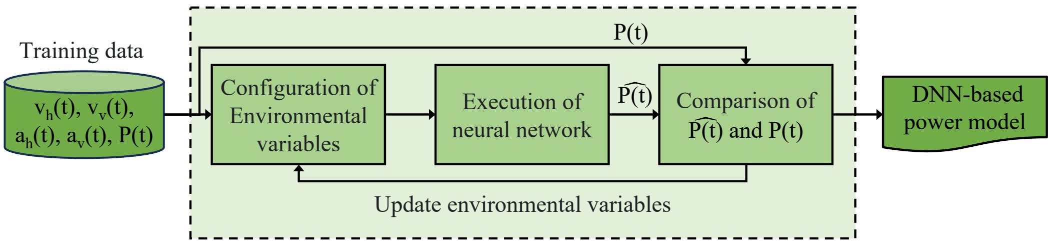

Figure 6. DNN-based power model training process.

3.3. Data-Driven Acceleration Model

To develop an accurate power consumption model, it is essential to train the neural network with as much data as possible. For UAV power consumption modeling, three-axis acceleration data are particularly critical to ensure the model's precision. However, in the flight power estimation process (as illustrated in Figure 1), only velocity information is provided as input to the flight power estimation process. $L(t)$, derived from flight synthesis, lacks vibration data, which are necessary for accurately capturing the impact of external factors like wind and the UAV's posture control adjustments. This vibration-related acceleration can only be obtained from UAV flight experiments. It is, of course, possible to construct a DNN-based power model using only velocity data for training from the outset. However, a model developed in this manner is significantly less accurate compared to one that incorporates acceleration data as an additional input. Acceleration not only reflects changes in velocity, but also captures the impact of external factors and posture control, leading to a more precise prediction of power consumption. To address this gap, we propose the acceleration modeling method, which analyzes the relationship between velocity and acceleration using flight experimental data. The acceleration model is separated into horizontal and vertical components to accurately reflect a UAV's dynamic behavior.

3.3.1. Horizontal Acceleration

Figure 7 shows the correlation between velocity and acceleration for horizontal flight. As velocity increases, acceleration also increases roughly, though with some variation. Based on the analysis of these flight experiment results, the acceleration model was constructed.

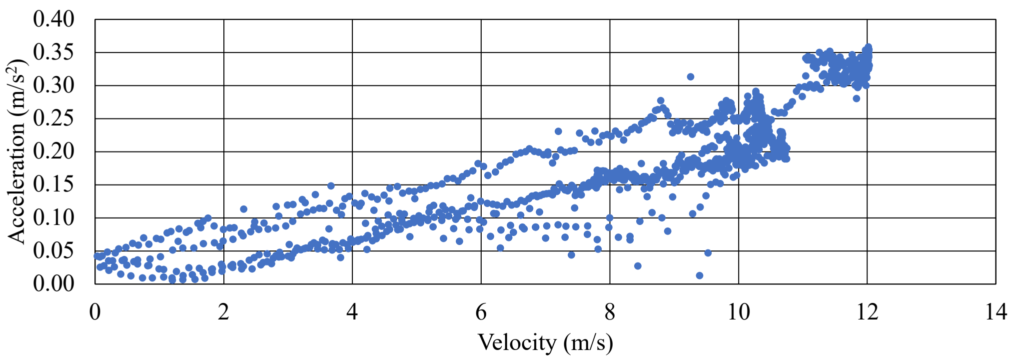

Figure 7. The correlation between velocity and acceleration in a horizontal direction.

After conducting sufficient flight experiments, multiple acceleration points were populated for a given flight velocity v_i, as shown in Figure 8. From these data points, the most frequent (largest population) value was selected as the representative acceleration value a_i at v_i. Similarly, for the next flight velocity v_{i+1}, the corresponding representative a_{i+1} was chosen. This allowed us to create a trend line connecting the representative acceleration values. Finally, a linear regression method was then applied to derive the linear acceleration model $a_h(v_h)$ as follows:

$$a_h(v_h) = \alpha v_h + \beta, \tag{3}$$

where α and β are extracted from the linear regression method.

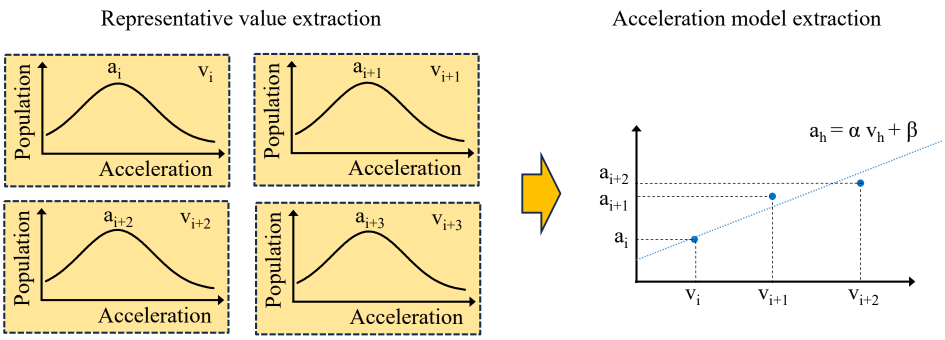

Figure 8. Derivation of the acceleration model.

3.3.2. Vertical Acceleration

Since most UAV operations involve maintaining a constant altitude, flight modeling in a vertical direction is typically minimal. However, when altitude changes occur freely during flight, the related energy consumption can be substantial, making it essential to model acceleration in the vertical direction. Most UAVs operate with a fixed torque in vertical flight for safety purposes. Accordingly, this paper modeled vertical acceleration based on UAV flight experiments.

The vertical velocity and acceleration exhibit distinct trends during ascent and descent due to the influence of gravity. As shown in Figure 9, t_{start} indicates the moment when the drone begins to ascend, $t_{\max\_acc}$ represents the point of maximum acceleration during the ascent, $t_{\max\_vel}$ corresponds to the point where the drone reaches its maximum velocity, $t_{\min\_acc}$ marks the point of minimum acceleration during deceleration, and t_{end} is when the drone comes to a complete stop, respectively.

The vertical velocity ranges from 1.5 m/s to 4.0 m/s, while the acceleration is constrained between 0.5 m/s^2 and 1.5 m/s^2. This results in an acceleration profile that forms a triangular shape, as shown in Figure 9. The profile can be expressed using the straight-line equations provided in (4), where each segment's slope is determined by dividing the change in acceleration (maximum or minimum) by the corresponding change in time ($\pm$1.5 or 0.5)/Δt. Furthermore, the α value is set to 0.5 for this particular drone model, which is a unique parameter that varies across different drone models.

This model demonstrates that the acceleration profile can be simplified and effectively predicted using only velocity data. By representing the acceleration with linear segments, the model reduces complexity while preserving the essential dynamics of vertical motion, making it both computationally efficient and practical for real-time applications.

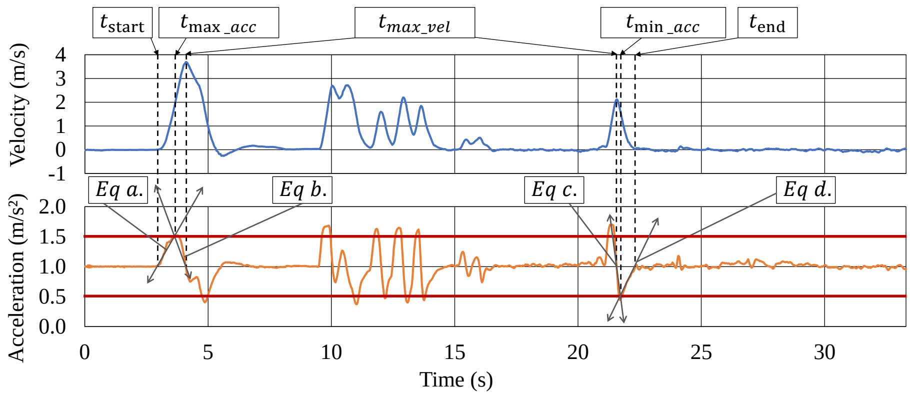

Figure 9. The correlation between velocity and acceleration in a vertical (up) direction (the IMU accelerometer defaults to 1).

$$a_v(t) = \begin{cases} \frac{\alpha}{t_{\max\_acc} - t_{\text{start}}} t + (1 - \frac{\alpha \times t_{\text{start}}}{t_{\max\_acc} - t_{\text{start}}}), & \text{if } t_{\text{start}} < t < t_{\max\_acc},\ \ Eq\ a. \\ \frac{-\alpha}{t_{\max\_vel} - t_{\max\_acc}} t + (1 + \frac{\alpha \times t_{\max\_vel}}{t_{\max\_vel} - t_{\max\_acc}}), & \text{if } t_{\max\_acc} < t < t_{\max\_vel},\ \ Eq\ b. \\ \frac{-\alpha}{t_{\min\_acc} - t_{\max\_vel}} t + (1 + \frac{\alpha \times t_{\max\_vel}}{t_{\min\_acc} - t_{\max\_vel}}), & \text{if } t_{\max\_vel} < t < t_{\min\_acc},\ \ Eq\ c. \\ \frac{\alpha}{t_{\text{end}} - t_{\min\_acc}} t + (1 - \frac{\alpha \times t_{end}}{t_{\text{end}} - t_{\min\_acc}}), & \text{if } t_{\min\_acc} < t < t_{\text{end}},\ \ Eq\ d. \\ +1, & \text{else.} \end{cases} \quad (4)$$

4. Experimental Results

4.1. Experimental Setup

In this paper, we utilized the DJI Phantom 4 Pro V2.0, a widely used UAV [16]. The UAV weighs 1.38 kg, with maximum horizontal and vertical velocities of 50 km/h and 18 km/h, respectively. Its maximum flight time is approximately 30 min. Figure 10 shows the UAV and controller, and Table 1 specifies the detailed information of the UAV.

Figure 10. DJI Phantom 4 pro [16].

Table 1. Specification of the UAV.

UAV Information	Values
Weight (including battery and propellers)	1.38 kg
Size (excluding propellers)	350 mm
Maximum velocity	50 km/h
Maximum flight time	30 min
Battery type	LiPo 4S
Battery size	5.8 Ah
Maximum charging power	160 W
Data collection frequency	30 Hz

A total of 640,000 data points were collected during approximately 6 h of flight experiments, consisting of 1.8 h in autopilot mode and 4.2 h in manual flight. Among these, the vertical flight time, horizontal flight time, and mixed vertical-horizontal flight time were 0.1 h, 3.6 h, and 2.3 h, respectively. During the flights, we collected various flight parameters, including three-axis velocity, acceleration, absolute altitude, and relative altitude from the IMU in the DJI monitoring system. For motor-related information, we recorded the angular speed, operating voltage, and current for each motor. A summary of the flight experiments is provided in Table 2.

Table 2. Summary of the flight experiments for the training of DNN.

Flight Information		Values
Altitude		0 to 60 m
Velocity	Average horizontal velocity	13.3 km/h
	Maximum horizontal velocity	48.2 km/h
	Maximum vertical velocity	17.0 km/h
Power	Average power consumption	310.4 W
	Maximum power consumption	1241.7 W
Energy	Overall energy consumption	1870.5 Wh

4.2. Flight Power Estimation Results

We first implemented three different power consumption models, as mentioned in Sections 2.2 and 3. Then, the accuracy of these three methods was compared to assess their performance.

4.2.1. Polynomial Power Model

Figure 11 shows the example flight data that were compared between the horizontal acceleration and related power consumption, where the vertical acceleration was less than 0.2 m/s^2. It was confirmed that there is a significant correlation between horizontal acceleration and power consumption. However, some discrepancies were observed in certain sections, which can likely be attributed to external factors such as strong winds during the flight. This indicates that the power consumption of the UAV was most closely related to horizontal acceleration.

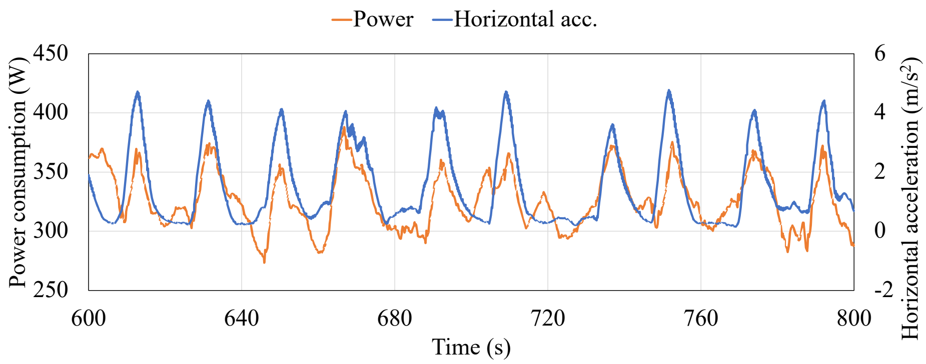

Figure 11. UAV horizontal acceleration and power consumption over 200 s.

It was confirmed that power consumption is primarily determined by horizontal acceleration if the UAV is flying in a horizontal direction only. Based on these findings, a simple yet accurate linear power consumption model was derived using the linear regression method as a polynomial form. Figure 12 shows the correlation between horizontal acceleration and power consumption over 6 h of flight data. The red line means the simple polynomial power model is based on the correlation. Most of the experimental data are distributed along the red line. However, as a_h decreases, the distribution of power consumption widens. This is due to the additional power consumption caused by vertical flight. The polynomial model (5) based on the experiment was obtained as

$$P = \alpha a_h(n) + \beta, \quad \text{where } \alpha = 16.39 \text{ and } \beta = 307.68. \tag{5}$$

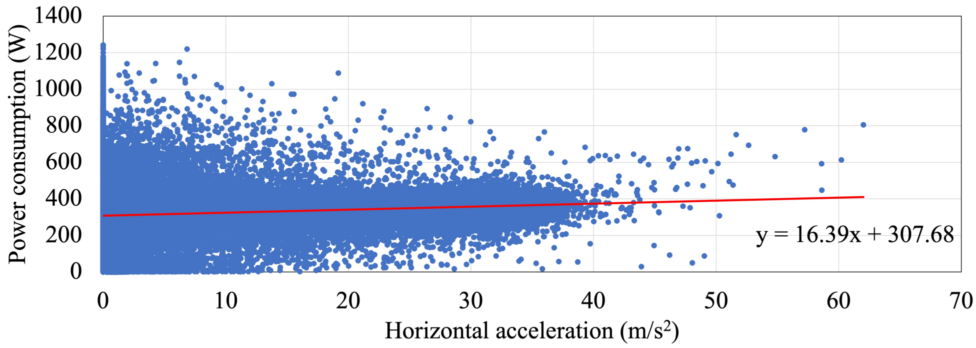

Figure 12. Trend line of the relationship between horizontal acceleration and power consumption.

Figure 13 compares the estimated power consumption derived from the polynomial model (blue color) with the measured value (orange color). The mean absolute percentage error (MAPE) by the polynomial model was 4.61%. In addition, the difference between the measured power and the estimated power was a maximum of 54.98 W and an average of 14.82 W. Overall, while the estimation result generally followed the measured values, the polynomial model failed to accurately estimate certain cases of lower power consumption. This is because the model does not adequately capture vertical flight or hovering, which significantly affects power consumption.

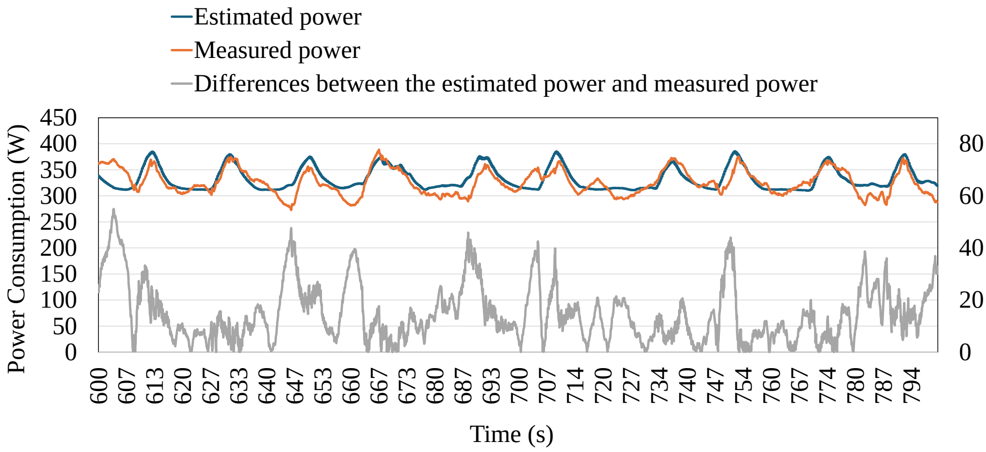

Figure 13. Validation in the polynomial model.

4.2.2. DNN-Only Power Model

To construct a DNN-only model, only the three-axis velocity was used as an input variable to develop the power consumption prediction model. Since power consumption can be predicted using only velocity information, this approach is well suited to the goal of UAV power estimation. Detailed information of the DNN training is specified in Section 4.2.3.

Figure 14 shows the discrepancy between the predicted power model and the measured results with the moving average applied. The MAPE was 11.28%, and the difference between the predicted power and the measured power was up to 163.89 W and 31.14 W on average. The significant difference between the measured and predicted results was primarily due to the model's inability to account for factors such as attitude control and the effects of wind. Therefore, to accurately model the power consumption of a UAV, it is essential to consider its acceleration.

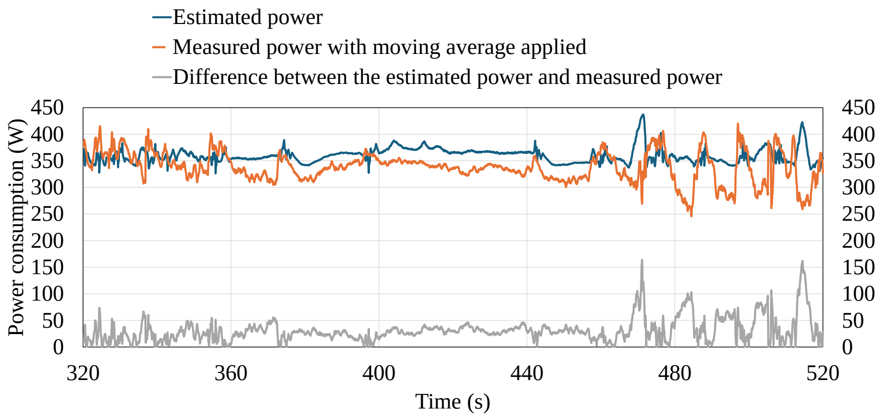

Figure 14. Validation in the DNN-only model.

4.2.3. Hybrid DNN-Based Power Model

In the proposed model shown in Figure 5, we separately constructed a DNN-based power model and a data-driven acceleration model. The DNN-based power model was implemented to estimate power consumption with UAV velocity and acceleration. Among the collected 640,000 data points, 95% were used as training data and 5% as test data. The output (independent variable) was set as the power consumed by the four motors, which was calculated using their operating voltage and current. Three different models were derived by varying the input (dependent variables): three-axis velocity and acceleration.

For training the DNN, the activation function was set as the rectified linear unit (ReLU) function, and the error was measured using the mean square error function. The Adam optimizer was employed for optimization. The number of nodes in each hidden layer was set to 30, and the network consisted of 50 hidden layers. These parameters were carefully selected based on the learning performance results.

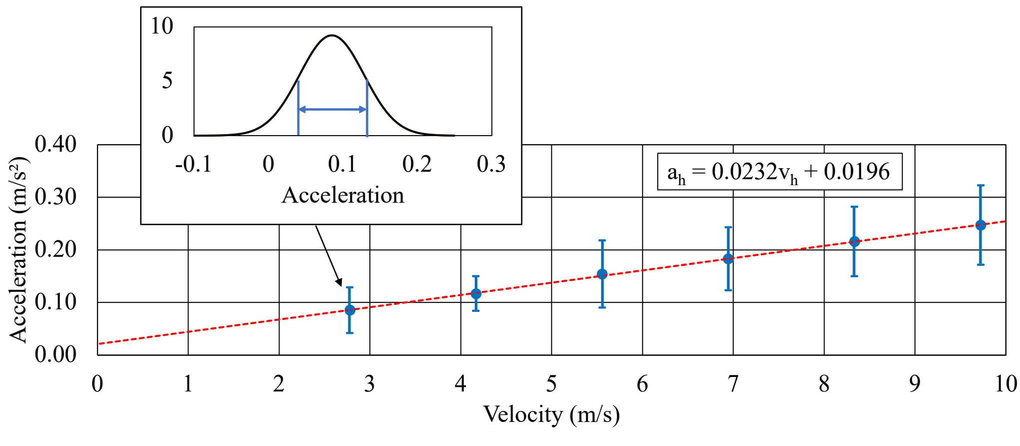

Figure 15. Modeling results of the horizontal acceleration.

The implementation of a data-driven acceleration model was performed based on the distribution of the acceleration in each UAV velocity. Figure 15 presents the modeling results for horizontal acceleration. Horizontal flight experiments were conducted at six different velocities (2.78 m/s, 4.17 m/s, 5.56 m/s, 6.94 m/s, 8.33 m/s, and 9.72 m/s). For each velocity, the populations of acceleration were analyzed. For example, the average, standard deviation, and highest population at 2.78 m/s were 0.085 m/s^2, 0.043, and 0.129 m/s^2, respectively. Each dot in the figure represents the highest population in each velocity, while bars at each velocity indicate the standard deviation above and below the highest population. The red dashed line represents the data-driven acceleration model a_h, as described in Equation (3).

4.3. Model Validation

We compared the following three different power consumption models, as shown in Section 4.2, for validation:

- LIN: uses a linear regression model to implement a polynomial power model.
- DNN: uses DNN with three-axis velocities only to implement a DNN-only power model.
- DNN + ACC: uses DNN with three-axis velocities and accelerations to implement the proposed hybrid DNN-based power model.

Figure 16 shows a part of the simulation results with three different models for a 30 min experimental UAV flight. The average and maximum horizontal velocities were 3.4 m/s and 11.46 m/s, respectively. The maximum velocities were −4.74 m/s for ascending and 3.98 m/s for descending. In the figure, dashed circles are used to for ascending and solid circles for descending. In the graph below, a blue line means measured power consumption as a golden reference, a dashed line means results obtained by the polynomial power model (LIN), a gray line means results obtained by the DNN-only power model with velocity inputs (DNN), and a red line means the proposed hybrid DNN-based power model (DNN + ACC).

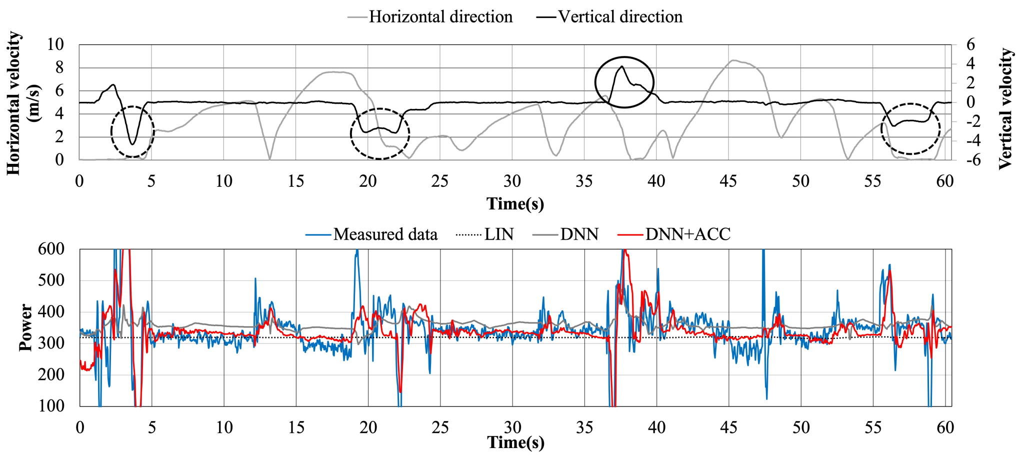

Figure 16. Model validation on 30 min flight experiments.

The RMSPEs for the LIN, DNN, and DNN + ACC models were 9.8%, 10.14%, and 6.12%, respectively, when compared to the actual power consumption. To calculate the mean squared error, the squared differences between the predicted and actual power consumption were computed for each time step at a sampling rate of 30 Hz. These squared errors were then averaged over the entire 30-min flight duration to derive the final error values for each model. LIN shows the power consumption by the change in the horizontal velocity. As such, it is nearly impossible to estimate the power consumption of flights in a vertical or mixed direction. But, on average for 30 min, the overall error was not too much because most of the flight time was horizontal flight. DNN and DNN + ACC followed the measured data over time, especially in the case of vertical movement. However, only DNN + ACC can expect the vibrations and peaks of the power consumption by horizontal and vertical acceleration. As a result, the proposed DNN+ACC showed a 39.45% more accurate modeling result when compared with DNN. In addition, in terms of energy consumption, the error rate was calculated to be 0.31% using the following formula:

$$Energy(J) = Power(P) \times Time(s). \tag{6}$$

This demonstrates the high accuracy of the proposed model in estimating energy usage during UAV operations. The corresponding analysis and results have been included in this paper to provide a clearer comparison between the simulation and experimental outcomes.

4.4. Optimization of the DNN-Based Power Model

The proposed power consumption model can be implemented not only on a server, but also onboard an UAV to determine the optimal velocity or the most efficient path for obstacle avoidance in real time. However, the primary challenge lies in the complexity of the DNN-based power model. For online power estimation, it is essential to not only estimate power consumption quickly, but to also maintain a sufficiently low resource requirement. Therefore, in this section, we discuss the optimal number of layers and the number of nodes per layer in DNN, balancing accuracy and computational speed.

Figure 17 shows the accuracy, runtime, and relative performance of the DNN for different configurations. The red values in the figure represent the baseline configuration with the highest performance for each evaluation metric, while the blue values correspond to the lowest observed performance. This comparison highlights the trade off between accuracy and computational efficiency for different DNN configurations.

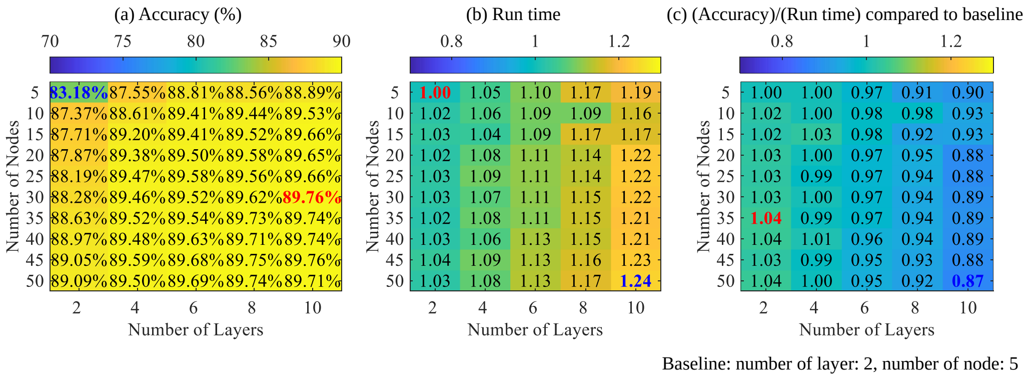

Figure 17. Modeling performance according to the number of layers and nodes.

Certainly, using a larger number of layers and nodes can improve the accuracy of flight power estimation. However, this also increases run time and resource consumption. Consequently, when considering both accuracy and run time, it was found that the optimal configuration consisted of two layers with 35 nodes per layer.

The selection of two layers with 35 nodes per layer in the proposed DNN-based power model was chosen after carefully evaluating the trade off between accuracy and runtime, as shown in Figure 17. In deep neural networks, the number of layers and nodes is typically determined based on the complexity of the problem, the characteristics of the input and output data, and the available computational resources. During our experiments, we observed that increasing the number of layers above a reasonable number of nodes only slightly improved the accuracy, while significantly increasing the runtime and resource consumption. Conversely, below about four layers, increasing the number of nodes per layer showed a more pronounced positive effect on the accuracy without significantly affecting the runtime. This suggests that, for this particular problem, the number of nodes plays a more important role in capturing the relationships in the data than the number of layers. By balancing these considerations, the configuration of two layers with 35 nodes per layer was found to achieve the optimal trade off between model accuracy and computational efficiency. This setup ensures sufficient complexity to model the UAV's power consumption accurately while maintaining the practicality required for real-time applications.

5. Case Studies

In this section, we apply the developed power model to various optimal flight problems. The first problem involves determining the velocity that minimizes energy consumption when flying a given distance. The second addresses finding the most energy-efficient path to reach a destination while avoiding a specified obstacle. For each problem, we compared the results derived from the proposed model with those obtained through actual experiments to evaluate the model's effectiveness in optimizing UAV flight.

5.1. Energy Consumption by Horizontal Velocity

Figure 18 shows the energy consumption by horizontal velocity between the measured data and simulation data. The flight distance was 100 m, and the altitude of the flight was 30 m. Blue dots mean the experimental results performed at 10, 15, 20, 25, and 30 km/h. A red line represents the simulation results achieved by the proposed hybrid DNN-based power model. It was confirmed that the estimated energy consumption at each velocity closely matched the experimental results. In addition, the simulation results showed that 30 km/h was the most energy-efficient velocity.

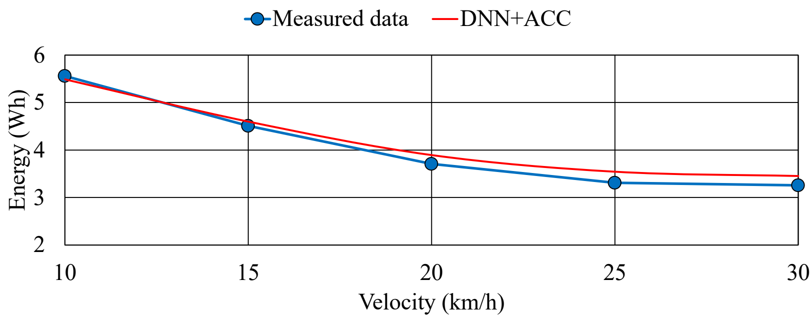

Figure 18. Comparison of the energy consumption by horizontal velocities.

5.2. Energy Consumption by Flight Route

In this section, we discuss the problem of finding the most energy-efficient path for a UAV to reach its destination while avoiding obstacles. Figure 19 shows four different flight routes from Location A to B when detouring through a flight blockage. A and B were placed H higher than ground, and the distance between the two was 77 m. Route 1 and 2 detoured through the blockage for 30 m in a horizontal direction, and it detoured through Route 3 and 4 for 30 m in a vertical direction. We assumed that the horizontal and vertical velocities in this case study were 4.5 m/s and 3.0 m/s, respectively. It is possible to know which route is the most energy efficient with the proposed power model.

Figure 20 shows the measurement results (block bar) and simulation results by the proposed power model (white bar). Route 3 was found to be the most energy-efficient flight route when considering both the measurement and simulation results. It is possible to pick the most efficient route with the proposed model even if there is some difference between the measured and simulated results. Additionally, overall, the predicted energy consumption data were smaller than the measured data. The primary reason for this discrepancy lies in the abrupt changes in the flight path, as illustrated in Figure 20. During the actual flight experiments, when the flight path changed direction suddenly, the UAV decelerated before accelerating to reach the target speed. This process resulted in higher energy consumption than what was predicted by the simulation.

As shown in Figure 19, Routes 2 and 4 involved sharp 90 degree turns, which required significant deceleration and acceleration. In contrast, Routes 1 and 3 followed smoother curves, resulting in less abrupt changes in speed. Consequently, as shown in Figure 19, Routes 2 and 4 exhibited a greater difference between the measured and predicted energy consumption when compared to Routes 1 and 3. This observation highlights the importance of accurately modeling sharp directional changes to improve prediction accuracy.

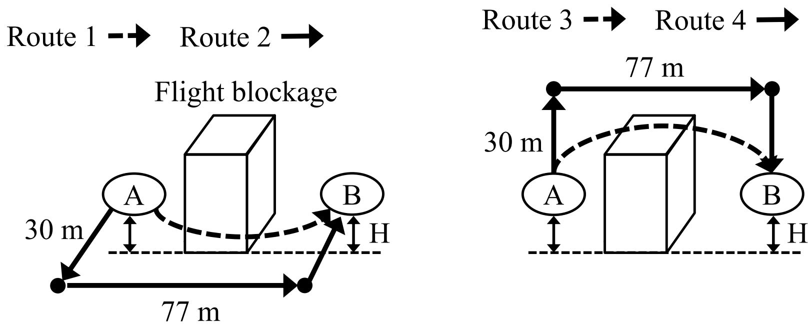

Figure 19. Optimal flight route decision problem.

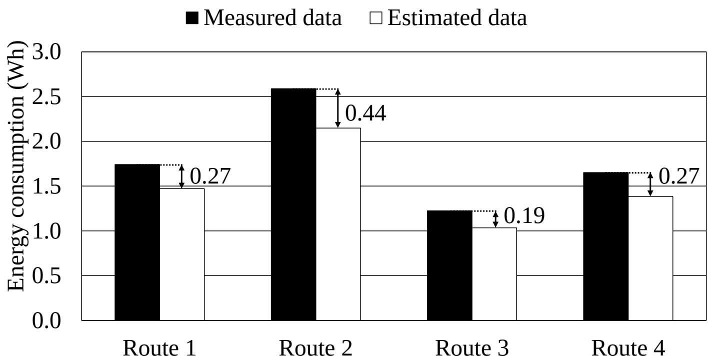

Figure 20. Measured and simulated results for different flight routes.

6. Conclusions

In this paper, we introduce a DNN-based power simulation framework, in which we suggest an empirical acceleration model that can fully utilize the accuracy of a DNN-based power model. To validate the proposed framework, we used a small quadcopter to extract the flight data and build power and acceleration models. The proposed power model was compared with other famous models with flight data for the validation. The proposed model is a good enough method that can be used to find the optimal flight profile, including velocity and route. To quickly check the availability of the proposed model, we applied it to three case studies, in which our model was validated in terms of how long it took to find the optimal horizontal velocity and optimal flight route with measured data.

Author Contributions: Conceptualization, M.K. and M.K.; methodology, M.K.; validation, M.K. and D.B.; formal analysis, M.K. and D.B.; writing—original draft preparation, M.K. and D.B.; writing—review and editing, Y.C. and J.K.; supervision, D.B.; project administration, D.B. All authors have read and agreed to the published version of the manuscript.

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