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Energy consumption and efficiency degradation predictive analysis in unmanned aerial vehicle batteries using deep neural networks

Luttfi A. Al-Haddad[1*], Andrzej Łukaszewicz[2*], Hasan Sh. Majdi[3], Andriy Holovatyy[4], Alaa Abdulhady Jaber[1], Mustafa I. Al-Karkhi[1], Wojciech Giernacki[5]

[1] Mechanical Engineering Department, University of Technology-Iraq, Baghdad, Iraq
[2] Institute of Mechanical Engineering, Faculty of Mechanical Engineering, Bialystok University of Technology, ul. Wiejska 45C., 15-351 Bialystok, Poland
[3] Department of Chemical Engineering and Petroleum Industries, Al-Mustaqbal University College, Hillah, Iraq
[4] Department of Computer-Aided Design Systems, Lviv Polytechnic National University, 79013 Lviv, Ukraine
[5] Faculty of Automatic Control, Robotics and Electrical Engineering, Institute of Robotics and Machine Intelligence, Poznan University of Technology, Poznan, Poland
* Corresponding author's e-mail: luttfi.a.alhaddad@uotechnology.edu.iq, a.lukaszewicz@pb.edu.pl

ABSTRACT

The unmanned aerial vehicles (UAVs) needs efficient energy management to ensure optimal performance and flight time. In this paper, the energy consumption and efficiency degradation in DJI Mini 2 drone batteries by the use of a deep neural network (DNN) for predictive analysis, was concern. The research conducted repeated flights and monitoring battery discharge from 100% to 27% over 20 trials. Experimental conditions, including flight duration and environmental factors, were controlled to ensure repeatability and to minimize any external influences on the recorded data. Data were stored onto AIRDATA (drone logbook) and then recollected for new labeling. The initial flights demonstrated similar, near constant performance, while following flights showed a gradual reduction in flight time (performance degradation). To ensure comparable power usage and minimize external influences, hover mode was selected for all flights. Next, on this data the DNN was trained using the metrics of mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), coefficient of variation of the root mean squared error (CVRMSE), and determination coefficient (R^2). The trained model achieved the MSE of 0.352%, RMSE of 0.593%, MAE of 0.324%, MAPE of 0.857%, CVRMSE of 0.743%, and R^2 of 0.981. The obtained results show the DNN's ability to predict future power consumption for the UAV that in turn provides insights for energy management and extension of battery life. The paper contributes to the development of sustainable UAV operations by better knowledge about battery performance for in-flight conditions.

Keywords: deep neural network; UAV; battery; flight duration; energy consumption.

INTRODUCTION

Background overview

The growth of the Unmanned Aerial Vehicles (UAVs) market of various sectors, including agriculture [1-4], logistics [5], surveillance & monitoring [6], have changed these areas by enhancing efficiency and reducing the UAV operational costs [7]. As UAVs become more popular, the need for reliable and efficient energy management systems, is observed [8]. The energy consumption of UAVs directly impacts their flight duration and operational range, which makes the battery performance a crucial factor for autonomous flights of these robots [9-10]. Lithium polymer (LiPo) batteries are widely used, especially in commercially available small drones due to the high energy density and low weight [11-12]. LiPo batteries degrade with each charge-discharge cycle and hence lead to reduced flight times. This degradation affects the performance and reliability of UAVs, and one needs to replace the batteries more often, which increase maintenance costs.

Given the critical importance of energy efficiency in UAV operations, there is a strong need to develop predictive models that can accurately predict battery performance and degradation. Such models would enable drone operators to optimize flight planning, enable better battery management, as well as extend the operational usability of UAVs. This study aims to address this need through machine learning techniques, specifically deep neural networks (DNNs), to analyze and predict the energy consumption and efficiency degradation of UAV batteries.

Literature review

The use of machine learning techniques to predict the remaining useful life (RUL) of Li-Ion batteries in UAVs is being explored intensively. Andrioaia et al. (2024) compared support vector machine for regression (SVMR), multiple linear regression (MLR), and random forest (RF) to predict the RUL [13]. The published research results showed that such models can be integrated into UAVs' predictive maintenance systems to prevent autonomy loss and accidents.

Mansouri et al. (2017) worked on the RUL estimation problem using a linear sparse model, support vector regression, a multilayer perceptron, and an advanced tree-based algorithm [14]. The approach was tested under various flight conditions and proved the effectiveness of machine learning in battery life cycle prognostics.

Manjarrez et al. (2023) proposed to use a fuzzy Takagi–Sugeno system optimized with particle swarm optimization to estimate energy consumption and flight time limits for UAV missions [15]. The methodology included an equivalent circuit model of the battery and an extended Kalman filter to determine the battery charge and achieved a maximum prediction error of only 2%.

Tang et al. (2020) developed a power transfer model-based method using a discrete-time state-space model to estimate the state of energy and predict the end of discharge time for Li-Ion batteries in rotary-wing UAVs [16]. The method integrated online measurements and a Particle Filter with Adam optimizer to enhance prediction accuracy. Ai et al. (2022) introduced a sequence-to-sequence model using a multilevel fusion transformer network to predict the RUL of agile UAVs [17]. The model achieved a prediction precision of 83% within 60 milliseconds and outperformed similar methods by the incorporating of an external factor attention and multi-scale feature mining.

Current gap and contributed novelties

Despite the significant advancements in the field of UAV battery management and predictive analytics discussed in the literature, several gaps that impede the full optimization of UAV operations, can be noticed. Research to date has primarily focused on the RUL prediction using various machine learning techniques, such as SVMR, MLR, and RF. While these methods have demonstrated effectiveness, they often lack the ability to accurately predict battery performance under dynamic and variable flight conditions, which is critical for daily UAV usage. Additionally, methodologies that employed fuzzy systems and state-space models have provided insights into energy consumption and flight time margins, however these approaches typically require complex parameter tuning and optimization, which may not be feasible in real-time applications. Although advanced models like sequence-to-sequence and transformer networks have shown promising results in RUL prediction, they are often computationally demanding and may not be suitable for all UAV platforms.

The current research gap lies in the need to propose a predictive model that combines accuracy, computational efficiency, and adaptability to various flight conditions. This study addresses these gaps by introducing a DNN model specifically designed to predict the energy consumption and efficiency degradation of UAV batteries. Unlike traditional models, the DNN approach uses extensive, historical flight data to learn complex patterns and interactions within the battery's discharge cycles. Thus, offering precise and real-time predictions. The novel contributions of this study include:

In-flight experiments with a hovering DJI Mini Combo 2 drone in the context of energy consumption. With the adaptation of a DNN, we achieved higher accuracy in predicting power consumption and battery degradation which outperformed traditional models. We proposed a comprehensive assessment on the performance degradation criteria of battery life cycle.

EXPERIMENTAL WORK

Selected drone and battery specifications

For this study, the DJI Mini 2 was selected [18-19], a widely recognized UAV that combines compact design with advanced technological features. The DJI Mini 2 is known for its lightweight structure which is less than 249 grams that corresponds. Its mass, dimension and high portability predefine it for various applications. Despite its small size, the drone is equipped with a 12 MP camera capable of recording 4K video at 30 frames per second, which ensures high-quality imaging. Regarding a flight performance, the drone offers a maximum flight time of 31 minutes under ideal conditions, which is achieved through its highly efficient power management system. It can reach a maximum speed of 16 meters per second in sport mode and can resist wind speeds of up to 10.5 meters per second. The drone utilizes the OcuSync 2.0 transmission technology with a transmission range of up to 10 kilometers with strong anti-interference capabilities. Additionally, it features dual-frequency (2.4/5.8 GHz) GPS + GLONASS for precise positioning and stable hovering, with hover accuracy of ±0.1 meters vertically and ±0.3 meters horizontally.

The power source for the DJI Mini 2 is a high-capacity LiPo 2S battery (82.5 g weight), which is integral to its performance. The DJI Mini 2's battery has a capacity of 2250 mAh and works at a voltage of 7.7 volts, providing 17.32 watt-hours. This battery supports up to 29 watts of charging power and is designed to operate within a temperature range of 5 °C to 40 °C, ensuring reliable performance across various environmental conditions. The battery also features built-in DJI Intelligent Battery Management System, which continuously monitors the battery status and provides real-time data to optimize performance and safety.

In-flight experiments and data recording

In the experimental phase of this study, a series of 20 hover flights using the DJI Mini 2 drone to analyze its energy consumption and battery performance, was carried out. Each flight was initiated with the battery fully charged to 100% and continued until the battery level dropped to 27%. The UAV platform and battery location are shown in Figure 1. Hover mode (so-called altitude hold mode) was chosen to ensure consistent power usage and to minimize external influences that could affect the drone's performance. During all flights in hover mode the altitude was set as 1.2 m above the ground. Moreover, in-flight experiments were conducted indoor in a noise-free room, where typical, observed in outdoor environmental

Figure 1. UAV platform used for in-flight experiments: DJI Mini Combo 2 and its battery location

effects, are very limited. It is worth mentioning that 27% was the percentage chosen to reach due to the memory capacity of the flight recordings excel file, which was necessary and scientifically enough for the current research.

During the flights, several critical parameters were recorded to provide a comprehensive dataset for analysis. These parameters included ambient and battery temperature, which were monitored to assess the impact of thermal conditions on battery performance. The current drawn by the drone was measured continuously to evaluate the power consumption during flight. Additionally, the remaining battery percentage was tracked in real-time to understand the rate of battery discharge. The data collection was designed to capture the nuances of the battery's behavior under controlled conditions which provided how various factors such as temperature and current draw affect battery efficiency and life. It is also important to point out that the UAV camera was operating to record the path for other purposes and research to be continuous with the current work, this means that the draining time of the battery was lessened due to the operating camera video.

Data collection and analysis

Data for this study was gathered using both the embedded flight logs of the DJI Mini 2 and the AIRDATA UAV platform [20–21]. The DJI Mini 2's flight logs automatically record comprehensive telemetry data, as depicted in Figure 2. This included battery status, flight duration, and power consumption metrics. This built-in capability ensures that all relevant data is captured accurately during each flight session.

To enhance the analysis, the flight logs were uploaded to the AIRDATA platform. AIRDATA provides advanced analytics and visualizations, allowing for detailed examination of the flight data. The platform offers tools to analyze temperature variations, current draw, voltage fluctuations, GPS coordinates, and battery health indicators. Using AIRDATA's capabilities, an in-depth analysis of the drone's power consumption and battery degradation over the 20 flights was performed. The integration of embedded flight logs and AIRDATA analytics ensured a comprehensive data collection process. This data was crucial for following training the DNN model. The details on the utilized DNN and methodology of predicting RUL is to be discussed next.

MATERIALS AND METHODS

Artificial intelligence (AI), particularly using DNNs, has revolutionized the field of predictive modeling and data analysis. In the context of UAV battery management, AI enables the development of sophisticated models that can predict power consumption and efficiency degradation with high accuracy. The ability to analyze complex patterns in large datasets allows DNNs to provide practical insights to optimize battery usage and extend the operational lifespan of UAVs. This predictive capability is crucial for maintaining the efficiency and reliability of UAV operations, especially in agriculture, logistics and industry, where precise energy management is prime important.

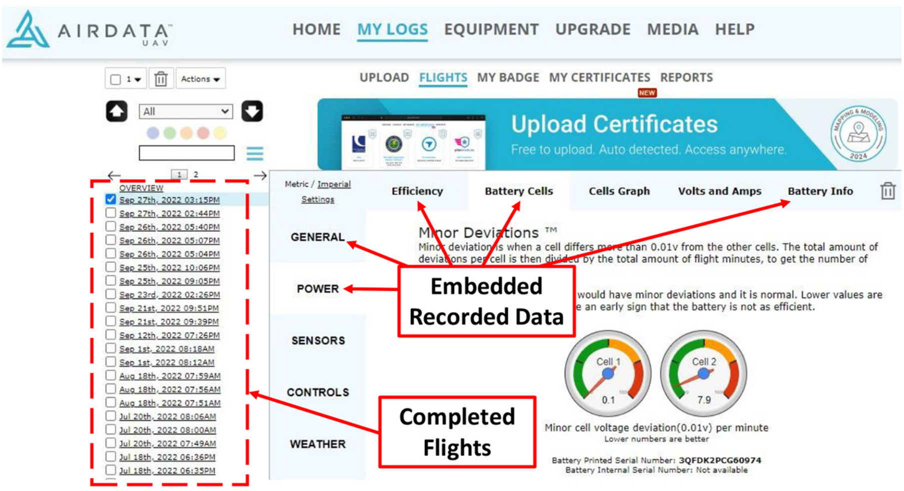

Figure 2. AIRDATA data access criteria

The designed DNN for presented research results in this paper has two hidden layers to balance complexity and computational efficiency. The network structure includes an input layer with five neurons that correspond to the input features: time (milliseconds), battery percentage, voltage of cell 1, voltage of cell 2, and battery temperature. The first hidden layer consists of eight neurons with a Rectified Linear Unit (ReLU) activation function, followed by a second hidden layer with four neurons, also using ReLU activation. The output layer has two neurons with which they represented the predicted total voltage and current, illustrated in Figure 3. This architecture was chosen to effectively capture the nonlinear relationships between the input features and the target variables, while maintaining a manageable model size for real-time applications. The following Table 1 summarizes the architecture of the DNN.

The DNN was trained on data from 80% of the experimental 20 flights and validated on the remaining 20%. To account for the time-dependent nature of the data, the sequential order of the flights was maintained in the training and validation datasets. This setup ensured that trends over time were learned by the model, enabling accurate prediction of unseen data, including the 100th flight.

To evaluate the performance of the DNN, several assessment metrics are used. These metrics provide a comprehensive understanding of the model's accuracy and predictive capabilities [22]. The mean squared error (MSE) measures the average of the squares of the errors, giving a sense of the magnitude of prediction errors. The root mean squared error (RMSE) is the square root of MSE as it offers a more interpretable measure of error magnitude in the same units as the target variables. The mean absolute error (MAE) reflects the accuracy of predictions and the Mean Absolute Percentage Error (MAPE) is useful for understanding prediction accuracy in relative terms. The coefficient of variation of the root mean squared error (CVRMSE) standardizes the error measure by dividing the RMSE by the mean of the actual values [23]. Finally, the determination coefficient (R^2) indicates the proportion of variance in the dependent variable that is predictable from the independent variables. All metrics used for complex assessment of model's performance are listed in Table 2.

The UAV power consumption is calculated using predicted values of voltage and current using Equation 1:

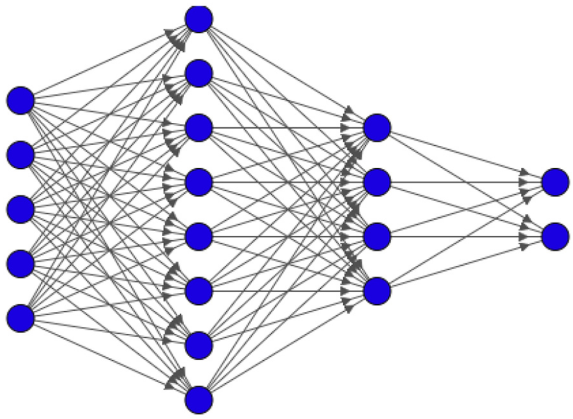

Figure 3. DNN architecture

Table 2. Assessment metrics used in the research presented in paper

Assessment metric	Mathematical expression
MSE	$MSE = \frac{1}{m}\sum_{i=1}^{m}(x_i - y_i)^2$
RMSE	$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(x_i - y_i)^2} \times 100$
MAE	$MAE = \frac{1}{m}\sum_{i=1}^{m}\lvert x_i - y_i \rvert$
MAPE	$MAPE = \frac{\text{RMSE}}{\bar{x}} \times 100$
CVRMSE	$CVRMSE = \frac{\text{RMSE}}{\bar{x}} \times 100$
R^2	$R^2 = \frac{\left(\sum_{i=1}^{m}(x_i - \bar{x})(y_i - \bar{y})\right)^2}{\sum_{i=1}^{m}(x_i - \bar{x})^2 \times \sum_{i=1}^{m}(y_i - \bar{y})^2}$

Table 1. DNN specifications

Layer	Number of neurons	Activation function
Input Layer	5	–
Hidden Layer 1	8	ReLU
Hidden Layer 2	4	ReLU
Output Layer	2	Linear

$$Power\,(W) = Voltage\,(V) \times Current\,(A) \quad (1)$$

and the efficiency degradation can be then calculated using Equation 2:

$$Efficiency\ degradation\ (\%) = \\ = \frac{Power\ (1st\ Flight) - Power\ (Nth\ Flight)}{Power\ (1st\ Flight)} \times 100 \quad (2)$$

where: n corresponds to the number of the flight.

In considered research to determine the RUL of the battery, the study simulates the conditions of the 100th flight and predict the time at which the battery will reach 27% capacity. Using the trained DNN, the model inputs the features of interest (time, battery percentage, voltage of cell 1, voltage of cell 2, and battery temperature) and obtain the predicted output voltage and current. By integrating these predictions over time, the flight duration until the battery achieved 27% is estimated. The degradation of battery capacity is analyzed by the decreasing flight times within multiple cycles and UAV flights. By comparing the predicted time for the 100th flight to reach 27% capacity with previous flights, the extent of capacity degradation can be quantified and predicted. This provides knowledge into the battery's life and performance trends over time.

RESULTS AND DISCUSSION

Experimental results

The data in Figure 4 recorded from the 1st, 10th, and 20th flights of the drone provide clear evidence of battery performance degradation over time. In the 1st flight, the drone took 1024.2 seconds (17.07 minutes) to reach 27% battery capacity. By the 10th flight, this time reduced to 999.8 seconds (16.663 minutes), and further decreased to 990.8 seconds (16.513 minutes) by the 20th flight. This progressive decline in flight time illustrates the typical behavior of LiPo batteries, which lose their capacity to hold a charge effectively with each charge-discharge cycle. The power consumption data shows a similar trend. During the 1st flight, the average power consumption was 41.195 watts. This value slightly decreased to 40.891 watts in the 10th flight and further to 40.717 watts by the 20th flight. This minor reduction in power consumption can be attributed to the increasing internal resistance within the battery cells, which leads to less efficient energy delivery over time.

The reduction in flight time, from 17.07 minutes in the 1st flight to 16.513 minutes in the 20th flight, highlights the need for accurate predictive models to forecast battery performance and ensure effective mission planning. By monitoring these parameters, UAV operators can provide optimal decisions about when to replace batteries or modify flight plans on the base of reduced battery capacity. To better show the progressing features, Figure 5 presents the experimental results for the 1st, 10th, and 20th flights of the DJI Mini 2 combo. Figure 5a shows the total voltage by illustrating a gradual decrease over following flights. Figure 5b presents the remaining battery percentages as it indicates the reduced time to reach 27% capacity from 17.07 minutes in the 1st flight to 16.513 minutes in the 20th flight. The total current in amps is shown in Figure 5c, while in the Figure 5d the battery temperature during flight, respectively.

Prediction of battery performance

The results of the DNN prediction/forecasting for the battery performance metrics are summarized in Table 3, which highlights key accuracy measures across following flights. Accordingly,

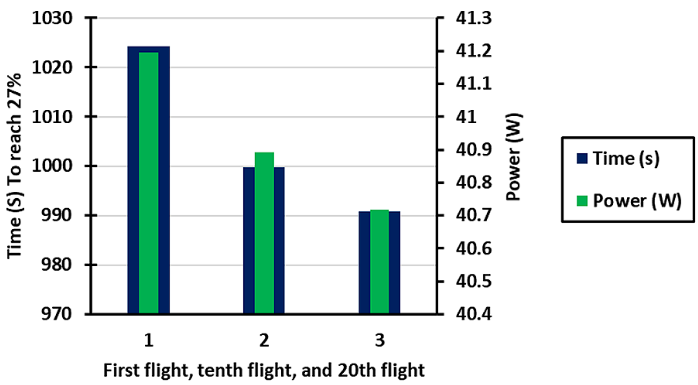

Figure 4. Selected flights times to reach 27% of the total battery capacity

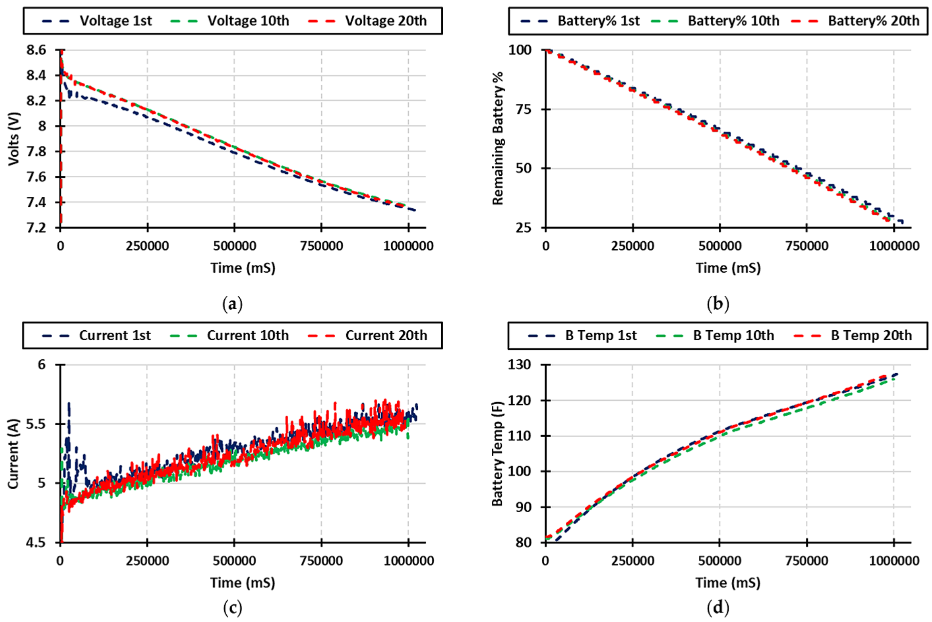

Figure 5. Experimental results of the three selected flights recorded, namely 1st, 10th, and 20th, respectively: (a) total voltage in volts; (b) remaining battery in percentages; (c) induced total current in Amps; (d) temperature of the battery during the operation until the percentage drops to 27%

Table 3. Comparison table of DNN forecasting results

Forecasted feature	Flight No.	MSE (%)	RMSE (%)	MAE (%)	MAPE (%)	CVRMSE (%)	R^2
Voltage	1st	0.352	0.593	0.324	0.857	0.743	0.981
Current		0.401	3.632	1.353	1.905	1.801	0.952
Voltage	10th	0.374	0.612	0.341	0.881	0.771	0.973
Current		0.423	1.654	0.366	1.924	0.923	0.951
Voltage	20th	0.387	0.621	0.354	0.889	0.781	0.965
Current		0.447	3.668	1.379	0.951	1.841	0.954

the table outlines MSE, RMSE, MAE, MAPE, CVRMSE, and R^2 for voltage and current across the 1st, 10th, and 20th flights. For the voltage forecast during the 1st flight, the model achieved accuracy with an MSE of 0.352%, RMSE of 0.593%, MAE of 0.324%, and a MAPE of 0.857%. The CVRMSE reached value 0.743%, and the R^2 value was 0.981. This indicates a very strong fit between the predicted and actual values. Conversely, the current forecast for the same flight demonstrated a higher level of error, with the MSE of 0.401%, RMSE of 3.632%, MAE of 1.353%, and a MAPE of 1.905%. The CVRMSE was significantly higher at 1.801%, and R^2 value was 0.952.

In the 10th flight, the voltage forecast results showed a slight increase in error metrics compared to the 1st flight, with an MSE of 0.374%, RMSE of 0.612%, MAE of 0.341%, and a MAPE of 0.881%. The CVRMSE increased to 0.771%, and the R^2 slightly decreased to 0.973. The current forecast for the 10th flight showed improved accuracy compared to the 1st flight, with an MSE of 0.423%, RMSE of 1.654%, MAE of 0.366%, and a MAPE of 1.924%. The CVRMSE was 0.923%, and R^2 value equal to 0.951, indicating consistent forecasting performance for the current. For the 20th flight, the voltage forecast maintained a similar trend with an MSE of 0.387%, RMSE of 0.621%, MAE of 0.354%, and a MAPE of 0.889%. The CVRMSE was 0.781%, and the R^2 value was 0.965, showing a slight decline in the model's predictive accuracy over time. The current forecast for the 20th flight showed an MSE of 0.447%, RMSE of 3.668%, MAE of 1.379%, and a MAPE of 0.951%. The CVRMSE was 1.841%, and the R^2 value was 0.954, reflecting a high degree of accuracy in the model's current predictions. Above results are graphically presented in Figure 6, which

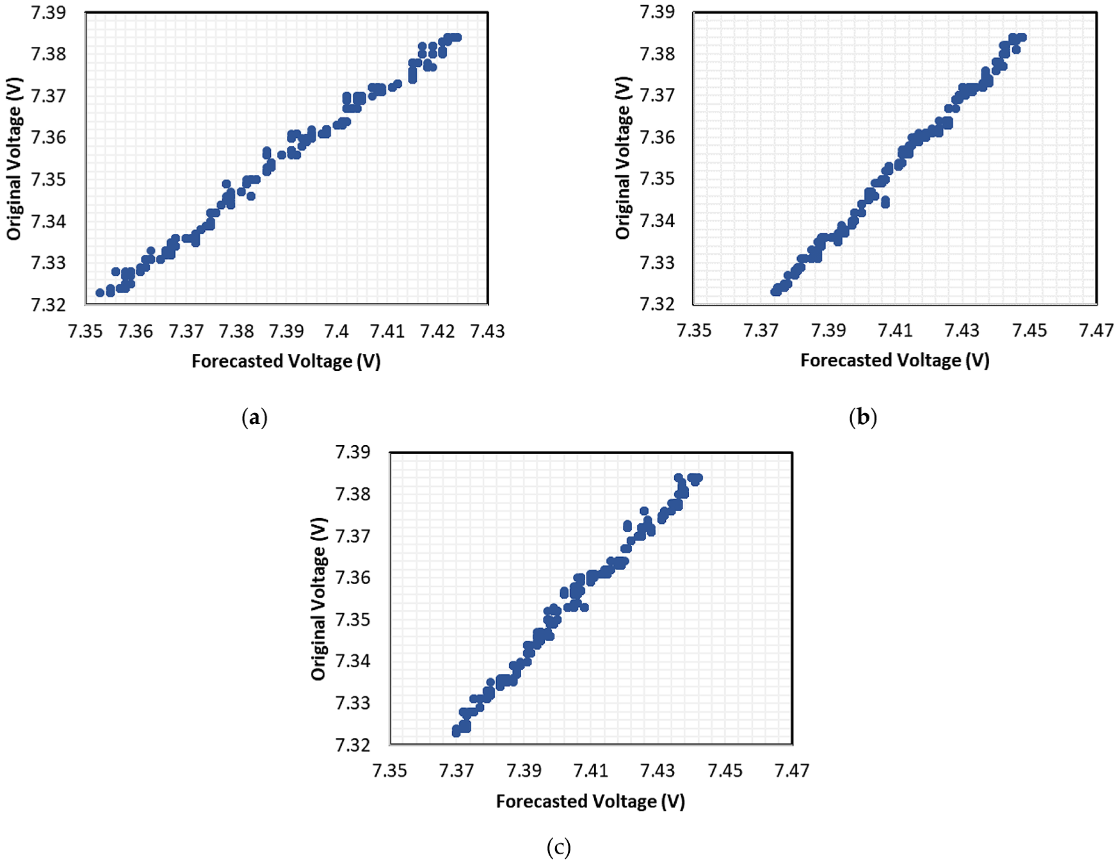

Figure 6. Total battery voltage regression lines: (a) 1st flight; (b) 10th flight; (c) 20th flight

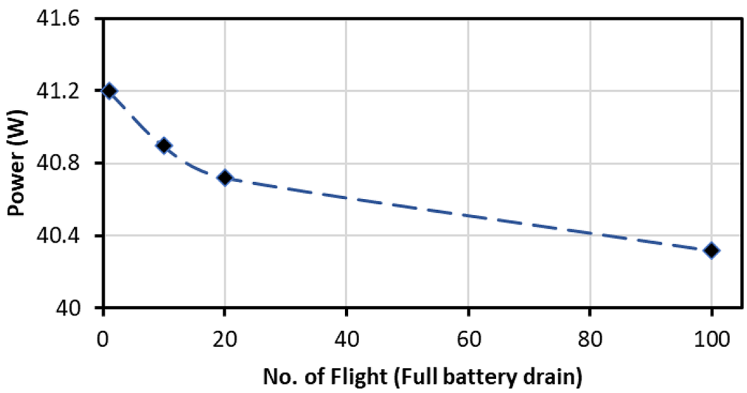

Figure 7. Power as a function of flight number

illustrates the total battery voltage regression lines for the 1st flight in Figure 6a, the 10th flight in Figure 6b, and the 20th flight in Figure 6c. The regression lines visually demonstrate the accuracy and predictive performance of the same DNN model across the different flight intervals.

Figure 7 illustrates the power consumption of the battery over a series of flights, specifically when the battery is drained until it reaches 27% capacity. The data points for the 1st, 10th, 20th, and 100th flights show a clear trend of decreasing power output over time. Initially, the power output starts at 41.195 watts for the 1st flight and gradually declines to 40.891 watts by the 10th flight and 40.717 watts by the 20th flight. By the 100th flight, the predicted power output further reduces to 40.313 watts. This descending trend shows a gradual degradation in battery performance, likely due to the wear and tear of the battery over multiple charging and discharging cycles.

Figure 8 demonstrates the efficiency degradation of the battery power over successive flights,

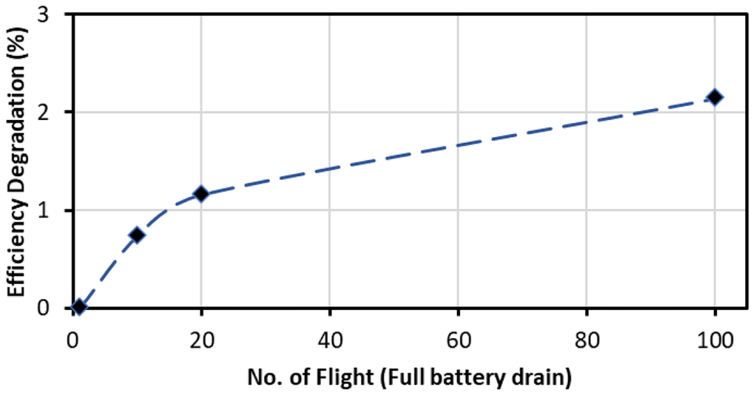

Figure 8. Efficiency degradation as a function of flight number

starting from the 1st flight. The power output for the 1st flight is the baseline at 41.195 watts, with no degradation. By the 10th flight, the power has decreased to 40.891 watts, representing a 0.74% efficiency loss. This trend continues, with the 20th flight showing a 1.16% decrease in efficiency at 40.717 watts, and by the 100th flight, the predicted power output drops to 40.313 watts, marking a 2.14% efficiency degradation. These data highlight the gradual decline in battery efficiency due to repeated usage.

CONCLUSIONS

In this study we investigated the energy consumption and efficiency degradation of DJI Mini 2 drone LiPo batteries using DNN to predict power and performance over multiple flights. The research began with the collection of empirical data, recording voltage and current readings across different flight sessions to form a dataset. In the presented research we used statistics and machine learning models, including DNN, to forecast voltage and current values for the 1st, 10th, and 20th flights with high accuracy. The DNN model demonstrated exceptional performance, as evidenced by low MSE, RMSE, MAE, MAPE, and CVRMSE values, alongside high R^2 values for both voltage and current predictions. For instance, the voltage prediction for the 1st flight had an MSE of 0.352%, RMSE of 0.593%, and an R^2 of 0.981. Furthermore, the study assessed the power consumption trend across following flights, revealing a steady descent in battery efficiency. The power output recorded was 41.195 watts for the 1st flight, 40.891 watts for the 10th flight, 40.717 watts for the 20th flight, and a predicted 40.313 watts for the 100th flight. This gradual decline corresponds to an efficiency degradation of approximately 2.14% by the 100th flight.

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