UAV Energy Consumption Prediction: A Comparative Study from Four Different Deep Learning Models

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***Abstract*—Unmanned Aerial Vehicles (UAVs) often face challenges that eventually occur with their power consumption, this is because UAVs have small battery capacity and continuous operating systems. To overcome this uncertainty, accuracy in predicting power consumption is needed so that UAVs can fly for a longer time. This study explores the prediction of UAV energy consumption using four different deep learning models, such as Long LSTM, GRU, LSTM-SA and GRU-SA. The results show that the model incorporating self-attention mechanisms, especially GRU-SA, significantly outperforms the other models, achieving the lowest MAE (0.0343), RMSE (0.0567) and MSE (0.0032). Self-attention improves prediction accuracy by focusing on important input features during dynamic transitions. This work highlights a strong foundation for improving UAV energy consumption.**

***Index Terms*—Self-attention, deep learning, energy consumption, prediction, GRU-SA**

I. Introduction

Focusing on the current trend, the rapid increase in the use of Unmanned Aerial Vehicles (UAVs) in various sectors such as industry, entertainment, military, and transportation has led researchers to conduct extensive research on this topic. Although UAVs have numerous advantages, their limited battery capacity and energy management are critical challenges that remain as major obstacles in their implementation [1]- [2].

The most visible challenge in UAV operations are the uncertainties of the surrounding environment. Energy consumption varies depending on several factors: these include weather conditions, load dynamics, wind speeds, and trajectory paths [3]. Moreover, the operational dynamics of UAVs complicate the measurement of energy consumption across various scenarios, underscoring the necessity for reliable predictions.

It is important to account for these uncertainties to ensure the safety and reliability of UAV operations. Accurate energy consumption predictions contribute to extended flight time of the UAVs, manage payloads, and implement effective contingency measures. Integration of deep learning with energy management systems enables precise prediction of energy consumption and production, thereby optimizing resource allocation to improve system performance. By improving energy efficiency and minimizing risks, accurate energy consumption predictions play a vital role in enhancing the scalability and reliability of UAV operations. [4]- [5].

Accurate prediction can also develop and improve energy allocation, expand flight time, and enhance reliability operation [1]- [3]. Research on UAV energy consumption prediction primarily focuses on three key areas: battery life prediction, anomaly detection, and power consumption forecasting. Among these, power consumption prediction is particularly crucial, as it directly impacts UAV efficiency and operational effectiveness, especially in dynamic environments [5].

Recent research focused on advanced hybrid modeling techniques for energy and battery management systems. Shahriar et al. proposed a hybrid RNN-CNN based model that combines Temporal Convolutional Networks (TCN) and Gated Recurrent Units (GRU) with attention on mechanism. This architecture effectively captures long-term and short-term dependencies in sequential data while focusing on important features to improve accuracy and robustness to noise [6]. In addition, Shahriar et al. applied machine learning approaches, specifically the Isolation Forest and Local Outlier Factor algorithms, to detect battery anomalies in the energy system. By analyzing features such as voltage, current, and temperature, this study achieved high accuracy in detecting outliers and anomalies that could compromise battery safety and performance [7].

Furthermore, Various methods have been proposed for UAV energy consumption prediction. These include traditional methods and advanced machine learning methods. Recent advances in UAV energy consumption modeling have explored and experimented with various approaches to improve prediction accuracy and efficiency. Cabuk et al. used an ensemble learning approach by combining Random Forest and XGBoost models to create a data-efficient energy consumption model for drone swarm operations. This method demonstrated high accuracy with minimal data requirements, making it suitable for scenarios with limited datasets [8]. Muli et al. then proposed an LSTM-based energy model designed to capture time-series data dependencies in UAV flight data, showing significant improvements in prediction accuracy compared to traditional mathematical models [9].

This study conducts a comparative analysis of UAV power consumption prediction methods, evaluating four the models: GRU, LSTM, GRU-SA, and LSTM-SA. Through in-depth comprehensive experiments and detailed analysis, the study assesses each model's accuracy and efficiency in forecasting UAV power consumption patterns. The primary objective is to identify the model that offers superior prediction accuracy and robustness in various UAV power consumption scenarios.

The structure of the paper is as follows. Section 2: the data collection, Section 3: the methodology, Section 4: Implementation, including training settings and results, Finally Section 5 Conclusion.

II. Dataset Description

The dataset utilized in this study is a publicly available flight dataset collected from a DJI Matrice 100 quadcopter [10]. It comprises detailed battery data and state measurements from 209 flights, covering approximately 65 kilometers with a total flight time of 10 hours and 45 minutes. The data collection includes numerous variations in ground speed, altitude, and payload weights, making it highly relevant for predicting energy consumption.

Among the 209 flights, 195 followed fixed triangular trajectories with variations in altitude (25 m, 50 m, 75 m, and 100 m), speed (ranging from 4 m/s to 12 m/s), and payload weights of 250 grams and 500 grams. These flights were repeated to ensure reliability. The remaining 14 flights were conducted on different paths from the others in order to be used for data testing. During each flight, high-resolution data—including inertial measurements, wind speed, battery voltage, and current—were recorded using onboard sensors [1].

III. Methodology

This section provides details the data preprocessing steps required to prepare the dataset for input into the models for the learning process. Additionally, it provides an explanation of the working mechanism of each model.

A. Data Preprocessing

To facilitate effective learning, data preparation is essential during the preprocessing phase. This involves reading the dataset and selecting the most influential features through feature engineering and selection, ensuring the data aligns with prediction requirements. Since the dataset lacks direct energy consumption data, We computed the total energy consumption of each flight by numerically integrating power over time [11]. Power (P) is calculated as the product of current (I) and voltage (V):

$$P = I.V \tag{1}$$

using the equation as follows:

$$E = \int P \, dt \tag{2}$$

In addition, the dataset has many features that can increase computational complexity. To overcome this, feature elimination is carried out using a Pearson correlation-based selection procedure. The Pearson correlation coefficient is used to measure the relationship between various features and target energy consumption, ensuring that only the most relevant features are used in the model. The equation for Pearson's correlation is as follows:

$$r = \frac{\sum (x_i - \hat{x})(y_i - \hat{y})}{\sqrt{\sum (x_i - \hat{x})^2 \sum (y_i - \hat{y})^2}} \tag{3}$$

After calculating the correlation using Pearson correlation, only a few features have a correlation value greater than 0.10 to the predicted target, energy consumption. Of the total 23 features available in the dataset, only 14 features were selected to be used in the model training process. These features include wind speed, state of charge (SOC), payload, and position (position x, y, z), orientation (orientation x, y, z), and velocity (velocity x, y, z). The selection of these features aims to reduce computational complexity while ensuring that the model uses the most relevant information to improve prediction accuracy.

B. LSTM and GRU Model

LSTM is an improvement of the simple RNN model. The vanishing gradient problem was successfully solved in the LSTM model through a number of modifications to its network architecture. In this study, we build the LSTM architecture by referring to the explanation in [9]. This model is proposed with the aim of improving the performance in capturing long-term dependencies by utilizing both forward and backward directions. The architecture uses two LSTM models combined in one layer, where one LSTM model serves as the forward layer and the other LSTM model serves as the backward layer.

GRU is a simple form of LSTM [12], where the forget gate is removed, but still maintaining the update gate and reset gate. These two gates are capable of carrying out functions similar to the three gates found in LSTM.

C. Self-Attention Model

Attention is a crucial aspect of human cognition, enabling us to focus on specific elements while filtering out less relevant information. Similarly, attention mechanisms in machine learning provide an effective solution for managing the dynamics of various features by assigning weights based on their relative importance. Among all attention mechanisms, in this study, we introduce the self-attention mechanism, a specialized form of attention that excels in establishing long-term dependency relationships. Usually apply the calculation method of Query vector (Q), key vector (K), and value vector (V). The main procedure is divided into 2 stages.

$$\begin{aligned} Q &= W_q X \\ K &= W_k X \\ V &= W_v X \end{aligned}$$

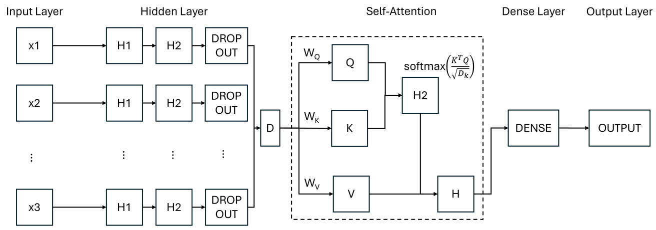

Fig. 1. The structures of LSTM-SA and GRU-SA

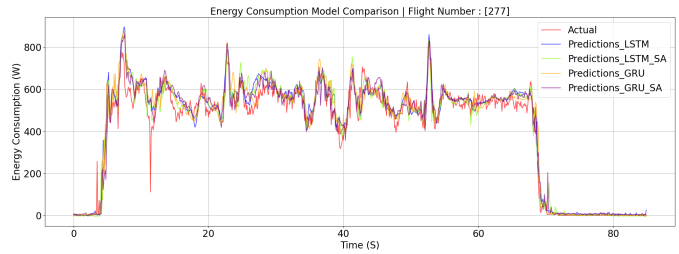

Fig. 2. Prediction results from four different models.

First, for each input X, use different linear functions to generate Q, K, and V vectors, and the calculation is shown as:

$$\mathrm{ATT}(Q,K,V) = \mathrm{softmax}\left(\frac{QK^\top}{\sqrt{K}}\right)V \tag{4}$$

Wq, Wk and Wv are the parameters metrics of linear transformation. Wq, Wk and Wv are the parameters metrics of linear transformation. Subsequently, the attention function is used to calculate the output vector H [13].

D. LSTM-SA and GRU-SA Model

This work adds a self-attention mechanism to LSTM and GRU models, named LSTM-SA and GRU-SA, to investigate whether it can help improve the UAV energy consumption prediction. The structure of LSTM-SA and GRU-SA is shown in Figure 1. Both models consist of three parts, namely the LSTM or GRU model, the SA module, and the fully connected layer. Since Gru and LSTM have almost the same structure, the same hyperparameters are used. This study also shows that each hidden size of LSTM and Gru is 128 [13].

IV. Results and Discussion

A. Training Settings

The training process in this study was conducted using the Python programming language with the TensorFlow library to implement and train machine learning models. Computations performed out on a computer with an Intel(R) UHD Graphics 770, Nvidia GeForce RTX 3060 GPU configuration, 1 TB storage capacity, and the Windows 11 operating system. To evaluate the model performance, four evaluation metrics are used: Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of determination R^2. These metrics provide a comprehensive assessment of the accuracy and reliability of the model predictions.

The input data was processed in batches of size 32 and converted into a sliding window format, in which each sliding window consisted of 100 time steps. The dataset was divided into training, validation, and testing sets in a ratio of 60:20:20.

Training uses the ADAM optimization algorithm with a learning rate of 0.001. The activation function used is Tanh as it produces outputs with a value range of -1 to 1, which is in accordance with the preprocessing applied to the data. All models are trained for 200 epochs to ensure convergence and stability of the results.

B. Results and Analysis

After the training modeling is done, we test the model using the testing data that has been separated in the training part. All models are done with the same conditions by predicting one flight, namely flight 277. Figure 2 shows the prediction results of all models combined. It can be seen that the model that had the added self-attention layer is closer to the actual value. However, if seen more up close, between the two LSTM-SA and GRU-SA models, the closest to the actual value is GRU-SA. This indicates that by adding a self-attention layer, the predictions produced could be improved. LSTM-SA's performance increases when there is a fast transition such as in the 40th second; However, it is undeniable that in both LSTM-SA and GRU-SA when reaching the peak there is a slight oscillation, indicating that this model is sensitive to noise in the high region. For models LSTM and GRU, both are capable of dealing with changes in energy consumption and are more dynamic. However, both are less precise and slow in capturing high variability.

TABLE I
PERFORMANCE EVALUATION OF DIFFERENT AI MODELS

Model	MAE	MSE	RMSE	R^2
LSTM	0.0347	0.0035	0.0588	0.9349
GRU	0.0378	0.0043	0.0656	0.9191
LSTM_SA	0.0350	0.0033	0.0578	0.9372
GRU_SA	**0.0343**	**0.0032**	**0.0567**	**0.9395**

The evaluation metrics values of all the models are shown in Table 1. It can be clearly seen that GRU-SA is the most outperforming model of all. However, it also appeared that the model when adding a self-attention layer resulted in a smaller value compared to before. Small MSE, MAE, and RMSE values indicate that the error between the actual values and the predicted values is small. Meanwhile, the r square approaching 1 indicates that the predicted values have a pattern that is more similar to the actual values. So it can be said that in this study, GRU-SA works better than other models in predicting UAV power consumption.

V. Conclusion

The limited battery capacity of UAVs remains a significant challenge, acting as a major obstacle to their widespread implementation. Predicting power consumption on UAVs using deep learning offers a viable solution to address these battery constraints. In this study, we compared the performance of LSTM, GRU, LSTM-SA, and GRU-SA models in predicting UAV energy consumption. The results demonstrate that incorporating self-attention improves the performance of both LSTM and GRU models by enhancing their ability to focus on critical features during transitions. This experiment highlights that combining GRU with self-attention significantly improves the accuracy and efficiency of UAV power consumption predictions, paving the way for more effective energy management in UAV operations.

ACKNOWLEDGMENT

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea Government (MSIT) (No. 2022R1A2C1007884).

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