Research on Duration Estimation of Rotor UAV Based on Flight Condition-Energy Consumption Identification

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Abstract. The quad-rotor UAV (Unmanned aerial vehicle) has a wide application market for its simple structure, easy operation and strong adaptability. During the flight, the endurance of UAV is an important parameter for flight planning, and it is of great significance to master the endurance capability of UAV. The endurance of UAV is mainly decided by the remaining capacity of the battery and the future energy consumption which changes with flight conditions. In this paper, a Flight Condition-Energy Consumption Model is established by analysing a large number of flight data with machine learning method, and the effects of different regression algorithms are compared. The validity of the model is verified by the actual flight. The endurance of the aircraft can be estimated using this model with the given remaining capacity of the battery and the future flight tasks.

1. Introduction
Nowadays, quad-rotor UAV has been widely used in civilian and military markets. In civilian market, the application of Rotor UAV in Aerial Photography, Environmental Monitoring, Agriculture, Power Line Inspection and other fields is increasing because of its simple structure, easy operation and strong adaptability [1]. Besides stable attitude control and excellent motion ability, better endurance of UAV is also required for practical application. The flight duration of UAV is an important index. To estimate the remaining flight duration of UAV accurately and to master its endurance capability is helpful for formulating UAV mission, improving effective flight time, ensuring safe return and landing of UAV, and so on [2]. For rotor UAV products on the markets, the existed functions of low-power warning and automatic return are mainly achieved by SOC estimation and minimum voltage setting of battery. For flight of rotor UAV, the endurance is not only determined by the battery capacity, but also closely related to the flight conditions, wind intensity and other factors [3]. With flight conditions considered, the remaining duration of UAV can be estimated more accurately.

Firstly, this paper analyses the flight conditions and forces of the Rotor UAV, and then excavates the relationship between the flight conditions and the energy consumption of the UAV with the method of machine learning. Afterwards, the actual endurance of UAV is estimated with the future mission, remaining battery capacity and the identified relationship. At last, the estimated endurance is revised with the wind intensity considered.

2. Analysis of Flight Conditions of Rotor UAV
Rotor UAV is composed of frame, power system, navigation system and control system. The power system includes battery, electronic speed control, motor and propeller, which provides and transfers energy to support UAV flight. Four-rotor UAV uses four motors to drive propellers to provide tension,
thus overcoming gravity and air resistance and realizing flight. The vast majority of battery power is supplied to motors and a small part to other equipment consumption in navigation and control systems. The speed of four motors is controlled by electronic speed control, which makes the attitude of UAV change. With the different attitude of UAV and the speed of motor, the propellers provide tension in different directions and sizes. Ultimately, UAV can achieve different flight states shown in the Figure 1, including hover, up and down motion, forward and backward motion, left and right motion and yaw motion.

![Figure 1. Different Flight Motions of UAV](image)

By monitoring the voltage and current of the battery of UAV, the remaining power of the battery can be obtained. However, the remaining power does not represent the duration. The duration of UAV needs to be predicted according to the future flight conditions and the relationship between flight conditions and energy consumption. It is very complicated to find the relationship between flight conditions and energy consumption from the physical point of view. It is necessary to calculate the pull force provided by UAV according to the flight status of UAV. Then the power of battery, namely energy consumption, can be obtained through propeller mode, motor model and electronic speed control model [4].

The simplest case is the hovering state of the Rotor UAV. The UAV withstands gravity and tension from propeller, and they are equal. The tension provided by the propeller can be expressed as

\[ T = C_T \rho \left( \frac{N}{60} \right)^2 D_p^4 \]  

(1)

Among all the parameters, \( C_T \) is the tension coefficient of propeller; \( \rho \) is air density; \( N \) is the rotate speed of propeller; \( D_p \) is the diameter of propeller.

\[ N = 60 \sqrt{\frac{G}{nD_p^4C_T\rho}} \]  

(2)

\( G \) is the gravity and \( n \) is the number of propellers.

\[ M = C_M \frac{G}{nC_T} D_p \]  

(3)

\( M \) is torque of the propeller and \( C_M \) is the torque coefficient.

\[ P = M \times N \]  

(4)

\( P \) is the mechanical power of the propellers. After obtaining the torque and rotate speed, the output power of the battery can only be obtained through the motor model, the electronic speed control model...
and the battery model [5]. The whole calculation process is complex and the efficiency of energy transfer needs to be considered, so that the final result may have a large error.

This paper uses a large number of flight data from the point of view of data and statistics, and determines the relationship between UAV flight conditions and energy consumption using the method of machine learning. In the NED coordinate system, the flight conditions of UAV can be described by the velocities and accelerations in three directions.

In the process of UAV flight, besides gravity and tension of propeller, UAV is also subject to air drag. For example, in the process of UAV flying forward at uniform speed, $F_D$ is the air drag and its expression is as follows:

$$F_D = \frac{1}{2} C_D \rho v^2 S$$

$C_D$ is the air drag coefficient; $S$ is the windward area; $v$ is the relative velocity between UAV and air.

Figure 2. Force Analysis of the Rotor UAV in forward motion

The output power of battery determines the mechanical power. From the equation 4, it can be seen that the mechanical power of the propeller is non-linear with the tension. Therefore, the power of the battery is mainly related to the tension. And from the Equation 5 and Figure 2, the tension is related to the square of velocity. Therefore, from a physical point of view, the output power of battery is related to the gravity, velocity and acceleration of UAV. In the process of machine learning, it is necessary to find meaningful condition characteristics such as the square of velocity according to the physical relationship between flight conditions and energy consumption.

Next, this paper will introduce several machine learning methods for regression prediction, and an energy consumption prediction model based on condition-energy consumption identification results will be established.

3. Machine learning algorithms for regression prediction

The energy consumption of UAV is continuous numerical data. Regression algorithm is needed in machine learning algorithm for condition-energy consumption identification. At present, the basic regression algorithms of machine learning are decision tree regression, linear regression, SVM (support vector machines), KNN (k-Nearest Neighbor algorithm) and so on. The ensemble learning algorithms mainly include boosting and bagging classes and random forest, which combine weak learners into strong learners and get better results. In addition, the neural network is also an algorithm used in regression prediction. The effect and performance of ensemble learning algorithms are generally better than that of basic regression algorithms. In this paper, GBDT, XGBoost, Random Forest, LightGBM and Neural Network are used to predict the data, and their prediction results are compared.

3.1. Gradient Boosting Decision Tree
Gradient Boosting Decision Tree is the full name of GBDT, is an improved learning algorithm based on gradient boosting machine and decision tree proposed by Friedman in 1999. The decision tree used by GBDT is Classification And Regression Tree, which uses variance to find the best partition point. The predicted value is the real mean value of all samples in the leaf nodes of the decision tree. The iterative process of GBDT is as follows: On the basis of the learner obtained after the last iteration, the negative gradient of the loss function of the model is used as a sample to minimize the loss function in this iteration step, and a new weak learner regression tree \( h_i(x) \) is fitted. The strong learner is updated to \( f_{i+}(x) + h_i(x) \) and the next iteration can be entered. The specific algorithm flow of GBDT is as follows:

1. The training set sample is \( T = \{(x_1, y_1), (x_2, y_2), \ldots (x_m, y_m)\} \), and the loss function is \( L(y, f(x)) \).
2. Initialize the weak learner as \( f_0(x) \).
3. For each iteration \( t = 1, 2, \ldots T \), the following calculation is performed for each sample:
   \[
   r_i = \left[ \frac{\partial L(y, f_i(x))}{\partial f_i(x)} \right]_{f_i(x)=f_{i-1}(x)}
   \]
   \( r_i \) is the negative gradient of the loss function of the learner updated in the last iteration, which is used as the predicted value of the sample in this iteration step.
4. Use new sample \( \{(x_1, r_{i1}), (x_2, r_{i2}), \ldots (x_m, r_{im})\} \) fitting a new regression tree \( t(x) \) and update the strong learner.
   \[
   f_i(x) = f_{i-1}(x) + h_i(x)
   \]
5. The final strong learner is the sum of all regression trees.
   \[
   f(x) = f_T(x) = f_0(x) + \sum_{i=1}^{T} h_i(x)
   \]

3.2. XGBoost

XGBoost is a scalable end-to-end machine learning system for tree boosting, and it can be considered as an improvement of tree boosting algorithm based on GBDT. The loss function of XGBoost includes not only training loss but also regularization term. The regularization term can control the complexity of the model, which helps to avoid overfitting. The first derivative of loss function with respect to \( f(x) \) is calculated as residual, which is used to generate a new decision tree in GBDT. But the model residual is obtained by calculate the first derivative and the second derivative of loss function with respect to \( f(x) \) using the method of Taylor expansion in XGBoost. In the fitting process of regression tree in each iteration, the method of finding the best segmentation point is different between XGBoost and GBDT. In addition, XGBoost has done a lot of other optimizations, such as proposing a novel sparsity aware algorithm for handling sparse data, combining cache access patterns and data compression andsharding to improve the efficiency of the algorithm and so on [6].

3.3. LightGBM

LightGBM is a framework based on gradient boosting launched by Microsoft in 2016, which also uses decision tree algorithm. The framework has the advantages of fast training efficiency, less memory and high accuracy. Conventional implementations of GBDT need to, for every feature, scan all the data instances to estimate the information gain of all the possible split points and to find the best partition point, which makes the training slow and consumes a lot of memory [7]. LightGBM improves these shortcomings accordingly:

1. GBDT uses pre-sorting algorithm when partitioning the tree nodes, which consumes a lot of space and time. LightGBM use a method which called Exclusive Feature Bundling. Instead of using all the features to scan to get the best segmentation points, some features are bundled together to reduce the dimension of the features in this method, which reduces the consumption of searching for the best segmentation points. The bundling of exclusive features uses the histogram-based
algorithm, and it discretizes the continuous floating feature values into k integers and constructs a histogram with a width of k. Finally, the histogram is used to find the optimal segmentation points for node partition.

(2) LightGBM uses a method called “Gradient-based One-Side Sampling” to calculate the gradient of samples. Instead of using all sample points to calculate the gradient, this method sample the samples to calculate the gradient, keep those samples with large gradients, and only randomly drop those samples with small gradients.

(3) In addition, the growth strategy of decision tree, optimal segmentation of feature values and parallel learning have been optimized in LightGBM.

3.4. Random Forest

In ensemble learning, Gradient Boosting class learners are generated by serial iteration, while Random Forest learners are generated in parallel, and there is no strong dependence between individual learners in Random Forest. The training methods of Random Forest algorithm are as follows: For datasets \{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\}, new T datasets are sampled by Bootstrap method and each new dataset contains m sample \{(x_{t,1}, y_{t,1}), (x_{t,2}, y_{t,2}), \ldots, (x_{t,m}, y_{t,m})\}. A basic decision tree is trained based on each new dataset, and all the basic decision trees are combined into an ensemble learner. When new sample is input, the result of random forest output is determined by the majority voting method based on the predicted results of each decision tree. Random feature selection is introduced into the training process of decision tree. When each node of the decision tree is split, a feature subset (usually the number of features is \log_2 k ) is randomly and uniformly extracted from all k features, and then an optimal splitting feature is selected from the subset to fit the decision tree.

After Random Forest algorithm is proposed by Leo Breiman, because of its good performance, the algorithm has been widely used in many fields such as bioinformatics, economic and financial fields, computer vision and so on.

3.5. Back-Propagation neural network

Multi-layer perceptron (MLP) neural networks are often utilized as estimation tools instead of the classical statistical methods. MLP neural network is a network structure formed by the interconnection of neurons, including input layer, hidden layer and output layer, which is shown in Figure 3. The input layer neurons receive external data input, the hidden layer and the output layer neurons deal with the data, and the final results are output by the output layer neurons. The learning process of neural network is to adjust the connection weight between neurons and the threshold of each functional neuron according to the training data.

**Figure 3.** The structural representation of MLP neural network

Error back propagation algorithm is the most successful learning algorithm of neural network so far. In forward propagation, the input signal is supplied to the neurons in the input layer, and then the signal is forwarded layer by layer until the result of the output layer is produced. If the output result
does not match the expected output, the error will be propagated backwards, and the connection weights and thresholds of neurons in each layer will be modified. Repeated training will be stopped until the output error meets the requirement.

4. The model of energy consumption prediction based on machine learning

4.1. Data preparation

Machine learning needs a lot of flight data, and the flight condition-energy consumption model is obtained by training the data. The Four-rotor flight data used in this paper is in “ulog” format, which includes position data, attitude data and battery data during flight.

4.2. Extraction of Features and Target Value

Machine learning is a process of training the relationship between features and target values. It is necessary to extract features and target values from sample data for training. In this paper, the features represent the flight condition of UAV and the target value is the energy consumption. It is necessary to use features to accurately describe the flight condition segment, and to ensure that the condition information will not be lost and distorted as far as possible. The flight conditions are described by the features in the time interval T and T is temporarily taken 0.5s. Many features related to velocity and acceleration can be selected before training begins. In the process of training, the features are adjusted according to the importance of features. The symbols and meanings of the final features after training are shown in the table 1 below.

| Feature Symbol | Feature Meaning (NED coordinate system) |
|----------------|-----------------------------------------|
| $V_{\text{mean}_N}$ | The mean velocity in the North direction |
| $V_{\text{mean}_E}$ | The mean velocity in the East direction |
| $V_{\text{mean}_D}$ | The mean velocity in the Down direction |
| $V_{\text{diff}_N}$ | The difference between the ending speed and the beginning speed in the North direction |
| $V_{\text{diff}_E}$ | The difference between the ending speed and the beginning speed in the East direction |
| $V_{\text{diff}_D}$ | The difference between the ending speed and the beginning speed in the Down direction |
| $V_{\text{mean}_{NE}}$ | The mean velocity on the North-East plane |
| $V_{\text{mean}_{NED}}$ | The total mean velocity |

The target value is the energy consumption $E_{\tau}$ in time period T, which can be obtained according to the voltage and current data in sample data.

$$E_{\tau} = \int_0^T (U \cdot I) dt$$ (9)

4.3. The training of sample data

After extracting feature data and target values from sample data, machine learning algorithm can be used for training. This paper uses the five machine learning algorithms introduced in Section 3 for training. There are 2217 samples in the sample set, 70% of which are trained as training set and 30% are tested as test set. The quality of the predict result is measured by three indicators, which are the determination coefficient $R^2$, the maximum deviation degree $E_{\text{max}}$ and the mean absolute error $E_{\text{MAE}}$. 
The determination coefficient $R_2$ is used to compare the predicted value error and the mean value error, and the prediction ability of the model is measured. The closer the predicted value is to the true value, the larger the $R_2$ is, and the maximum value is 1.

$$E_{\text{max}} = \max\{\text{abs}(y_i - \hat{y}_i)_{i\in\{0,n-1\}}\}$$

Considering that the model should be applied to the energy consumption identification during the flight, there can be no large error, otherwise the final remaining duration estimation will be deviated greatly. $E_{\text{max}}$ cannot exceed the maximum tolerance.

$$E_{\text{MAE}} = \frac{1}{n}\sum_{i=0}^{n-1}|y_i - \hat{y}_i|$$

The mean absolute error is the average difference between the predicted value and the real value, and also represents the accuracy of the prediction.

In the training process, the parameters of the algorithm are adjusted by controlling variables to get a better prediction model.

### 4.4. Experimental result

| Algorithm model                  | $R_2$  | $E_{\text{MAE}}$ (W·s) | $E_{\text{max}}$ (W·s) |
|----------------------------------|--------|-------------------------|-------------------------|
| GBDT                             | 0.8733 | 1.632                   | 4.098                   |
| XGBoost                          | 0.8794 | 1.602                   | 4.116                   |
| LightGBM                         | 0.8691 | 1.657                   | 4.138                   |
| Random Forest                    | 0.8707 | 1.630                   | 4.194                   |
| Back-Propagation neural network  | 0.8579 | 1.694                   | 4.235                   |

According to the training results in Table 2, it can be found that the performance gap of the five algorithms on the test set is not very large. The maximum deviation degree of the target value prediction results is about 4, the mean absolute error is about 1.6, and the determination coefficient $R_2$ is about 0.87. The number of hidden layers and the number of neurons in each layer of the neural network have a great influence on the prediction results, and LightGBM has the fastest training speed. Considering comprehensively, the prediction model of GBDT is selected for subsequent application.

![Figure 4. The predicted and actual values of GBDT in 100 samples randomly selected](image1)

![Figure 5. The absolute value of the predicted and actual errors of 100 samples](image2)
Figure 4 shows the situation of the predicted and actual values of GBDT in 100 samples randomly selected from the test set, and Figure 5 shows the absolute value of the predicted and actual errors of 100 samples, and ranks them. The results show that the prediction errors of most data samples are very small.

![Feature importance of different models](image)

**Figure 6. Feature importance of different models**

Figure 6 shows the feature importance of LightGBM, GBDT, XGBoost and RF training models. The proportion of feature 3 and feature 6 is larger, because the lift motion of UAV has the greatest impact on energy consumption.

4.5. **Energy consumption revision considering wind power**

The air resistance caused by wind has a great impact on the flight energy consumption of UAV. It is necessary to obtain wind data during flight and revise the predicted energy consumption. The air resistance of UAV is caused by the relative velocity of UAV and air as shown in equation 5, and only horizontal direction is considered. In the case of wind, the airspeed of UAV is the vector difference between ground speed and wind speed. At this time, the air resistance is equal to \( F \)

\[
F = k(\tilde{v}_{\text{ground}} - \tilde{v}_{\text{wind}})^2
\]

(13)

\[
k = \frac{1}{2} C_D \rho S
\]

(14)

The coefficient \( k \) is related to damping coefficient \( C_D \), air density \( \rho \) and windward area of airframe. The damping coefficient and air density can be considered a constant, and the windward area can be obtained by the current attitude of UAV. So in the actual flight process, the air resistance \( F \) can be calculated according to the current wind speed and direction in the case of windy. Combining the displacement \( \Delta x \), the energy consumption \( E \) obtained from flight condition prediction is revised to \( E_{\text{rev}} \).

\[
E_{\text{rev}} = E + \tilde{F} \cdot \Delta \tilde{x}
\]

(15)

5. **Estimation of flight duration for the UAV**

Through the training of the flight condition-energy identification model, combined with the remaining capacity and cut-off voltage of the battery, the remaining endurance estimation of the UAV can be performed.
When the remaining capacity or voltage drops to a certain level, it means that the battery can no longer maintain normal flight and the UAV must complete landing before that. In this paper, we consider the estimation of the residual duration for the mission scenario which the future mission is known. When the flight mission is known, the future flight conditions of UAV, including speed, acceleration, flight duration, and so on of each flight condition, can be obtained from the flight mission [8][9]. According to the flight condition-energy consumption model, the energy consumption of each flight segment can be known, and the remaining battery capacity need be combined to estimate whether the mission can be completed. The UAV's mission over a period of time is shown below:

1. It rises uniformly at a speed of 1m/s for 5 seconds.
2. It hovers at fixed point and fixed altitude for 10 seconds.
3. It flies at a constant speed of 4 m/s along the North-axis keeping the altitude unchanged for 5 seconds.
4. It lands uniformly at a speed of 1 m/s for 5 seconds.

![Figure 7](image1.png) Figure 7. The predicted power and actual power in flight

![Figure 8](image2.png) Figure 8. The predicted energy consumption and actual energy consumption in flight

The Figure 7 and Figure 8 respectively show the power and the energy consumption during flight, including the predicted value according to the flight condition, the actual value, the maximum and minimum predicted values. As can be seen from the figures, the actual value of flight is within the error range of the predicted value based on the flight condition. By predicting the energy consumption required for the mission and combining the current residual capacity of the battery, it can be estimated whether the mission can be completed in the future.

When the flight mission is unknown, the average energy consumption of UAV can be estimated by using the flight condition data of UAV in the past period of time. It replaces the energy consumption in the future flight process. In this case, the accuracy of the remaining duration cannot be guaranteed, so more safety landing time margins need to be set up to avoid UAV accidents during flight [10].

6. Conclusion
This paper analyses the flight conditions and the corresponding different energy consumption. Based on a vast amounts of flight data, this paper establishes the Flight Condition-Energy Consumption model using machine learning method, and compares the results of different regression algorithms such as GBDT, LightGBM, Random Forest and so on. According to the actual flight data, the predicted energy consumption is compared with the actual energy consumption, which proves the validity of the model. Based on the flight condition-energy consumption model, combined with the remaining capacity of battery and the future flight mission, the endurance of UAV can be estimated.
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