Predicting UxV Operation Time using Machine Learning Approach for IoBT Mission Completion

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Abstract

Battlefields in the 21st century depend heavily on the proper use of the Internet of Things (IoT) devices rather than sending soldiers physically on critical missions. The IoT devices that are connected and supported on the battlefield scenarios are known as the Internet of Battlefield Things (IoBT). The usage of unmanned any vehicles (UxV) on the battlefield (e.g., unmanned aerial vehicles (UAVs), unmanned ground vehicles (UGVs), Unmanned underwater vehicles (UUVs), etc.) is very significant as they can be controlled remotely without any person on board. However, due to the limited battery capacity of these devices, they can be stopped at any time, especially during the time of any crucial mission on a battlefield. Therefore, predicting the total operation time is decisive in completing a mission and enhancing the quality of service. This study presents a unique idea of predicting the operation time of the UxV devices using a machine learning (ML) approach on IoBT. A comparison of different ML algorithms has been analyzed to find out the most significant technique based on accuracy. Moreover, new research directions are also discussed as future work of this research.

Ⅰ. Introduction

The IoT devices are utilized in battlefield scenarios to form the Internet of Battlefield Things (IoBT) and complete critical missions where no soldier needs to go physically to complete the task. Rather than sending the soldiers, different IoT devices like unmanned any vehicles (UxVs) (e.g., unmanned aerial vehicles (UAVs), unmanned ground vehicles (UGVs), Unmanned underwater vehicles (UUVs), etc.) can be dispatched from the base station and controlled these devices from a remote location to reduce the losses of soldiers lives. However, due to the limited battery capacity, the UxVs can not provide service for a longer period [1]. Before sending the UxVs in any mission, estimating the total service time of a particular device is crucial. Unfortunately, the manufacturer mentions the no-load servicing time when they consider the maximum output. Most of the time, the output prediction is not up to the mark. Additionally, some environmental parameters are also responsible for degrading the performance of every UxV device. In the state-of-the-art, Sayani et al. [2] proposed an intelligent framework to predict the flying time based on the different payloads in a UAV. However, the author considered only the payload with the DJI drone. Additionally, the author did not represent the accuracy rate between the original and predicted flight times. Authors from [3,4] proposed different techniques to determine the running time of lithium-ion batteries, considering the state of health and the state of the capacity of a particular battery. However, the authors did not mention any exact model to predict and compare the service time of different UxV devices. Therefore, no methods or algorithm is still available to predict the UxV's total servicing time based on the historical data before sending it to any critical mission on a battlefield. As a result, it is necessary to find a suitable technique to predict the servicing time of any UxV device before sending it to any critical mission on the battlefield..

Ⅱ. Proposed Methodology

Fig. 1. Mission Scenario for battery prediction.

Fig. 1 displays the exemplary architecture for the proposed idea. The UxV devices are dispatched in different directions to collect different data from the battlefield. As the UxV devices are fully controlled from a remote location, the battery capacity can be degraded over time. However, the UxV devices can be dead or useless on the run time due to the battery capacity in different critical missions. Therefore, to correctly predict the total servicing time of the UxV devices, one unique dataset can be prepared, and different machine learning models can be applied to get the most acceptable outcome.

III. Result Analysis

For a simple case scenario, one UAV is used to create a dataset that contains more than 500 data. Fig. 2 represents the real-time flying image of a Parrot Bebop 2 for both inside and outside environments. An open refine tool has been used to discard inconsistencies from the dataset, such as missing values, error-prone values, inaccurate data, duplicate values, etc. The dataset contains different attributes like the age of the battery, weight of the battery, flying heights, the wind of the area, the temperature of the area, total load, and total flying time. The UAV has flown more than 500 times to create the whole dataset.

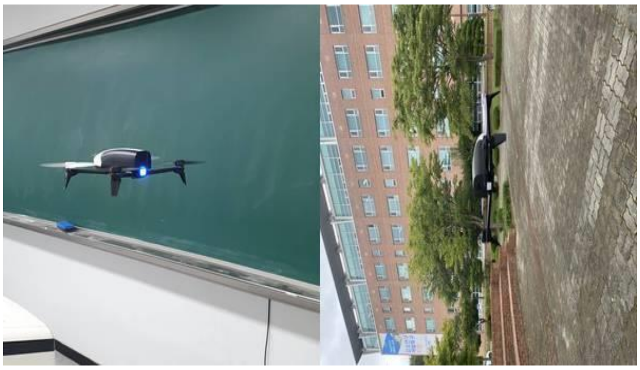

Fig. 2. Real-time Parrot Bebop 2 UAV Flying Image

To identify the best algorithm for predicting the total servicing time, the Matlab simulation tool has been used to process the data from the prepared dataset. As the flying time is a numeric value, supervised ML techniques have been applied to get the best result, specifically the regression analysis. It is necessary to identify the independent variables that have a significant correlation with the dependent variable to improve the fitness of the regression analysis. Four different regression techniques have been applied to find the best one for experimental purposes in this scenario. After loading the dataset in MatLab, 70% of the data is used to train the model, and 30% of the data is used to validate. Table 1 represents the result analysis of the experiments using different types of machine learning (ML) models.

Algorithms	R^2 Values
Linear Regression	0.93%
Polynomial Regression	0.90%
Gradient Boosted Tree	0.88%
Simple Regression Tree	0.89%

From the result analysis, it has been shown that the linear regression model is the best one compared to the polynomial regression, gradient-boosted tree, and simple regression tree based on the R2 value. The true response and predicted response from the experimental analysis are shown in Figure 3. Therefore, after calculating the servicing time of any UxV using the linear regression technique, these devices can be sent to avoid any kind of uninterrupted issue during the critical mission. The UxV can successfully complete any critical mission on a battlefield if the servicing time can be predicted earlier.

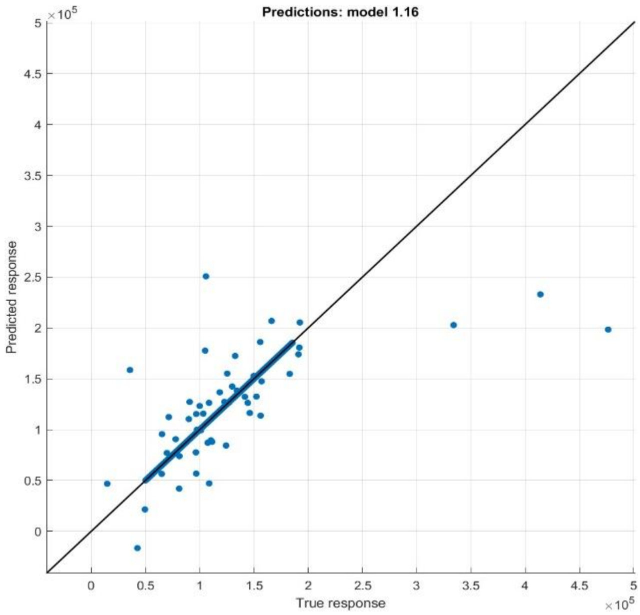

Fig. 3. True Response vs. Predicted Response.

IV. Conclusion and Future Work

An The servicing time of unmanned any vehicle (UxV) iscrucial to predict before sending it on a battlefield for a critical mission. This paper compares different ML algorithms and analyzed that linear regression is the most useful algorithm to predict the servicing time before sending any UxVs. For the experimental purpose, the unique dataset is created using only the UAV which is a part of UxV. Additionally, in the future, other UxV devices like an unmanned ground vehicles, Unmanned underwater vehicles can also try to run and collect the servicing time to enrich the dataset. Besides, deep learning models can also be analyzed to find out a more precise result to improve this research.

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