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Obtaining Condition Monitoring Data for the Prognostics of the Flight Time of Unmanned Aerial Vehicles

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Abstract

In recent years, the use of Unmanned Aerial Vehicles (UAVs) that can fly at low and medium altitudes has become widespread in the world. Knowing the airtime and the maximum range that the UAVs, which are used in critical missions, especially in the military field, are important for the reliability of the mission to be carried out. Therefore, in this study, the creation of a data set to calculate the flight time and range of the UAV using the prognostic method, which is one of the heuristic methods, is discussed.

For this purpose, a fixed-wing UAV was used in this study to create the data set to be used in the prognostic methods. The UAV used in flights has a weight of 2.5 kg, a wingspan of 1.3 m, and a body length of 1 m. In addition, thanks to the control card used in the UAV, both manual and autonomous flights were made. The flight data of the UAV was transferred to the Ground Control Station (GGS) instantly.

As a result, data sets were obtained from manual and autonomous flights to be used in the prognostic method. By using these data sets, it will be possible to calculate the duration and range of the UAV in the future flights.

1. Introduction

Unmanned aerial vehicles (UAVs) have become popular in many civilian and military fields in recent years due to their potential to be used in challenging and critical areas and to offer solutions in a wide range of applications.

The remaining flight time of UAVs in the air depends on the payload, the length of the mission range, the capacity of the battery used in the UAV (Konar, 2019), atmospheric conditions such as temperature, pressure and wind, and many parameters (Arik et al., 2018, Oktay et al., 2018). However, one of the limitations of UAVs during the flight time is that this dependence constantly changes according to the flight environment (Coban, 2019, Coban et al., 2019, Mátyás et al., 2019).

For this reason, the use of UAVs in critical missions that require high flight time is unreliable. Unexpected discharge of the battery of the UAV during flight will result in loss of material and equipment, and more importantly, the failure of the intended mission. As a result, the need for reliable diagnostic and prognostic models that can predict the current Battery Health Status (BHS) and Remaining Flight Time of the UAV is increasing day by day. Studies in this field are of great interest both in the literature and in practical applications (Schacht-Rodríguez et al., 2019).

BHS is one of the critical parameters regarding how much energy is left in the battery. It is used as a diagnostic measure in batteries, as it is accepted as the basic building block of BHS's battery management system. (Andre et al., 2013). However, this diagnostic may not be used to directly measure the condition of the battery.

For this reason, a number of battery diagnostic approaches have been proposed in the literature, such as the voltage-temperature thermal runaway method (Tran et al, 2022), the median expectation-based diagnostic approach (Khalid et al., 2015), the Bayesian statistical approach (Saha et al., 2007), the ampere-hour integral method (Yang et al., 2015), the particle filtering approach (Yan et al., 2017), the open-circuit voltage method (Lee et al., 2008), the extended kalman filter (Wu et al. al., 2016).

Remaining Useful Life (RUL) is defined as the time when the performance of equipment used in a system first falls to the failure threshold (Zhang et al., 2018). If RUL can be predicted with high accuracy, precautionary measures can be taken to repair and maintain the equipment used. Model-based and data-driven methods can be used in RUL methodologies (Hu et al., 2014).

Lithium-Polymer (Li-Po) batteries, which are frequently used in UAVs, have a nonlinear and time-varying dynamic electrochemical process throughout the discharge process. Therefore, the use of model-based approaches in Li-Po batteries may not be useful in practice, as too many parameters and complex calculations are required during the discharge process. (Eleftheroglou et al., 2019). As a result, model-based approaches are mostly used for theoretical research and battery status determination (Lin et al., 2015). Data-driven approaches, on the other hand, do not require prior knowledge of the physics of the system, as they rely on measured data to derive the discharge process of Li-Po batteries.

In this study, it was aimed to obtain data sets for data-based prognostic methods. In order to realize this aim, a fixed-wing UAV has been produced. After the production, the manual and autonomous flight tests of the UAV were successfully carried out, and useful data were obtained to be used in the data-based prognostic model, and these data are presented in the third section. In the last section, conclusions and discussions are given.

2. Materials and Methods

Aviation started in the early 1900s and developed rapidly in parallel with technological developments. However, as a result of the globalization and modernization experienced in the field of technology in the world in recent years, the production of UAVs which is a new type of aircraft operating in many fields has begun. Demands for cheap and practical aircraft are increasing day by day, especially in military and civilian areas. These increasing demands have reduced the need for manned aircraft. Produced UAVs can perform high-risk missions without putting the pilot's life in danger unnecessarily. For this reason, UAVs have become an important industry for many military and civil aircraft manufacturers. In addition, UAVs have become one of the remarkable research areas for academia in terms of cheap cost and accessibility (Keane et al., 2013).

Today, UAVs, which have many different types and areas of use, are mostly classified according to their weight and the maximum altitude they can reach. Nano UAVs, which have the lowest value in terms of flight weight and altitude are generally used in tracking and monitoring in the military field. Micro UAVs with a flight weight of between 100g and 1000g and a flight altitude of less than 500 feet are mostly flown as a hobby. The UAVs used in this study with a flight weight of between 1 kg and 20 kg and a flight altitude of less than 5000 feet fall into the category of mini UAVs. Tactics, which have higher values according to flight weights and flight altitudes, are frequently used in military and agricultural spraying areas in Medium Altitude Long Endurance and High Altitude Long Endurance UAVs.

In this section, the UAV and the components of the UAV produced for the study are introduced. In addition, the importance of the method used is presented.

2.1. Produced UAV and Components

The UAV produced for this study is fixed wing. The UAV, which has an overhead wing and a standard tail configuration, has a body length of 100 cm, a wingspan of 130 cm and a weight of 1400 g. The main reason for using fixed wing UAV in this study is that the flight characteristics are quite stable. In addition, it can easily perform the desired tasks in autonomous flights. The fuselage view of the fixed-wing UAV is given in Figure 1. There is sufficient space inside the body for the placement of electronic components. It is aimed that all necessary electronic cards, sensors and batteries to be used for this purpose can be easily placed inside the body. For the body of the UAV, it was made using depron material with a thickness of 6 mm and a density of 30 kg / m^3. Depron body is covered with model coating. In Figure 2, the 3D model of the UAV drawn in the computer environment is given.

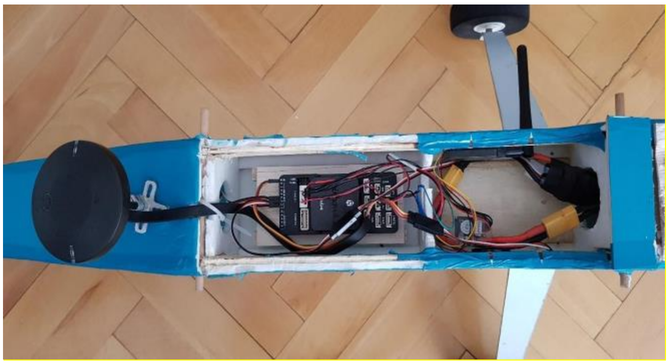

Figure 1. Electronic components of the produced UAV inside the body

The propulsion of the fixed-wing UAV produced is provided by a 1100 Kv brushless electric DC motor. The power required for the flight of the UAV is provided by a 3-cell Li-Po battery with a capacity of 3300 mAh and a discharge value of 25C.

In fixed-wing UAV systems, propellers are needed to get the thrust from the engine. Unlike other aircraft, this issue is of great importance in single-engine fixed-wing aircraft. Considering this situation, the compatibility of the engine, Electronic Speed Control Unit, propeller and battery used in the study is very important.

Pixhawk Cube, one of the stable and safe flight control cards with open source code system, was chosen for the flight control card used in the study. The Pixhawk Cube, which has a dual-core processor, meets the high processor capacity needed for the planning of autonomous flights required for this work. In addition, a telemetry system capable of broadcasting at 433 MHz is connected to the Pixhawk Cube used in the UAV. The telemetry system can provide data transfer directly compatible with the Pixhawk Cube. In addition, the flight data of the UAV can be monitored directly over GGS with APM planner and Ground Control software on the computer.

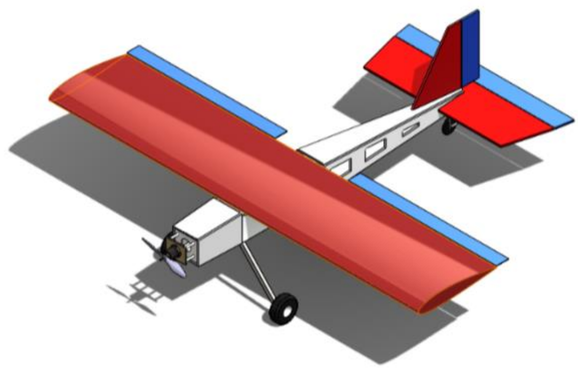

Figure 2. 3D model of UAV

2.2. Importance of the Method Used

It is important that the user can monitor the flight data that affects the performance of the UAV. The most important of the flight data obtained is the battery status data. Therefore, it is important to monitor the change in the voltage value of the battery in real time. Depending on the type of battery used, each battery has a different threshold. If the battery voltage drops below the threshold value, deterioration may occur in the battery cells. As a result, battery life will be greatly reduced. The threshold voltage value for Ni-CD batteries, which are frequently used in UAVs, is 1.2 Volts, while the threshold voltage value for Li-Po batteries is 3.7 volts. If the flight operation continues below this threshold value, it will not be possible to use the battery properly. Li-Po batteries are packages created by the combination of many cells. The breakdown of any cell in the pack will directly affect the total voltage of the battery.

The amount of current drawn from the battery used in the UAV directly affects many different flight parameters of the UAV. Chief among these are the flight speed of the UAV, its altitude and the number of revolutions of the engine mounted on the UAV. The more these parameter values increase, the more the current drawn from the battery will increase accordingly. As a result, the remaining useful life of the battery will be reduced.

The produced UAV needs to climb to a certain altitude in order to perform its flight in a healthy way after the moment of take-off. This propulsion is provided by the brushless DC motor attached to the UAV. The power required for the rotation of the motor is provided by the Li-Po battery.

One manual flight and one autonomous flight data graph are presented from the flight tests. The diagram of how the data is received and transferred during the flight is given in Figure 3.

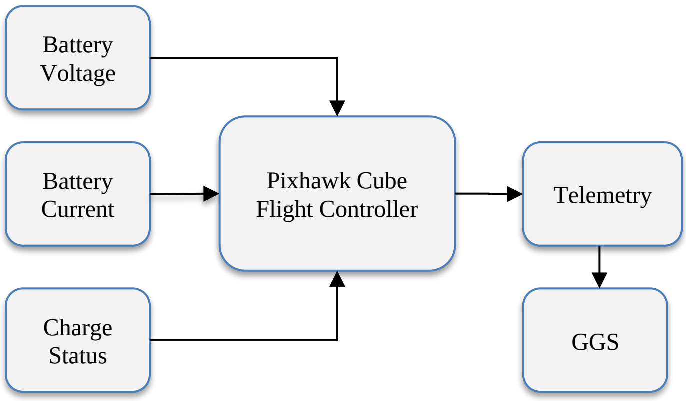

Figure 3. Scheme of receiving data from the UAV

3. Implementation Phase

During the successful flight tests of the produced UAV, many different parameters such as battery voltage from the controller inside the UAV, current drawn from the battery, percent capacity of the battery, flight altitude, air temperature and air pressure at the time of flight were successfully transferred to GGS. Among these parameters, the effect of battery voltage, current drawn from the battery and the percent capacity of the battery on the flight time of the UAV has been observed. Many flight tests were carried out within the scope of the study. The main charts created from the Pixhawk Cube flight control card and post-flight data are included in this section. The obtained data sets can be used to calculate flight time (seconds, sec) and range in data-based prognostic methods.

The image of the UAV taken before the manual and autonomous flight on the model airstrip is given in Figure 4. Their routes are shown in Figure 4, respectively.

Figure 4. Pre-take-off image of the produced UAV

Figure 5, Figure 6, Figure 7 and Figure 8 show the routes of the first, second, third and fourth flights performed manually on the Talas Municipality model airstrip, respectively. In Figure 9, the flight route performed in autonomous mode is given. Thus, the flight routes of the UAV became visual. The blue lines represent the flight path of the UAV in stabilized mode, the red lines represent the flight of the UAV in manual mode, and the purple color represents the flight of the UAV in the autonomous mode.

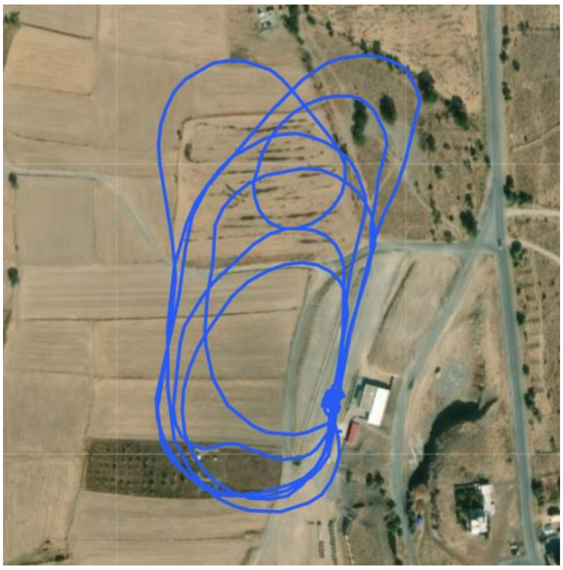

Figure 5. The 1st flight route of the UAV

Figure 6. The second flight route of the UAV

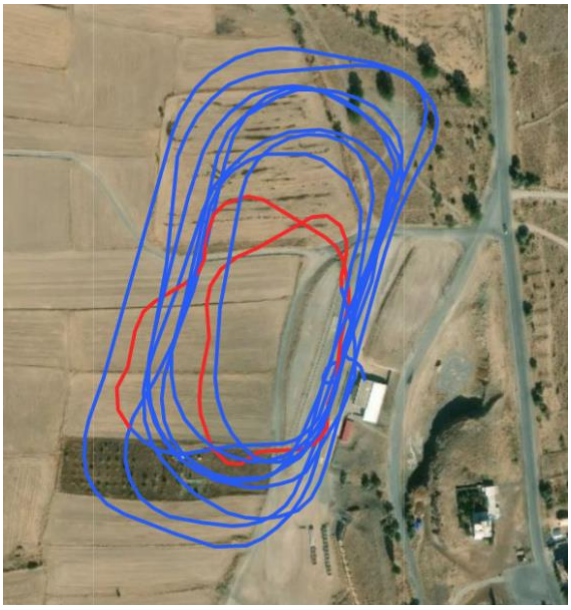

Figure 7. The 3rd flight route of the UAV

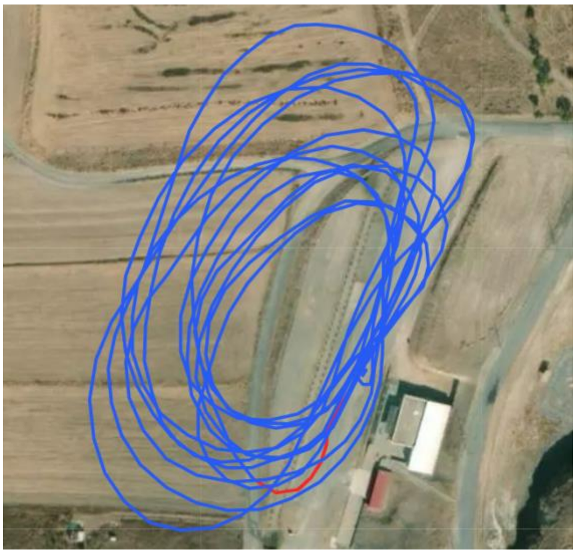

Figure 8. The 4th flight route of the UAV

Figure 9. The 5th flight route of the UAV

In Figure 10, Figure 11, Figure 12, Figure 13 and Figure 14, the current-time graphs drawn from the battery during the flight time of the UAV are presented. It has been observed that the current drawn from the battery increases up to 25 Amps (A) when instantaneous power is drawn from the UAV for propulsion. In this way, the flight characteristics of the UAV can be estimated by looking at these data. As a result of the data received, no unusual situation was observed in the battery.

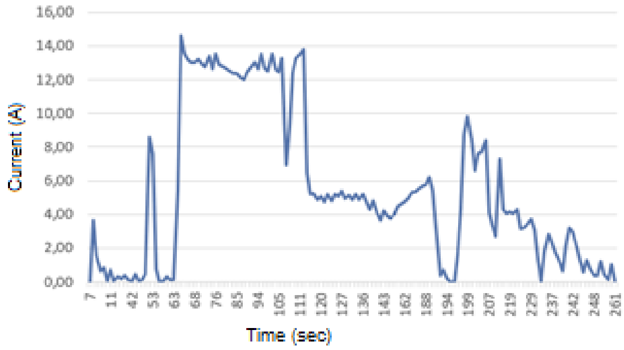

Figure 10. Current-time graph of the 1st flight of the UAV

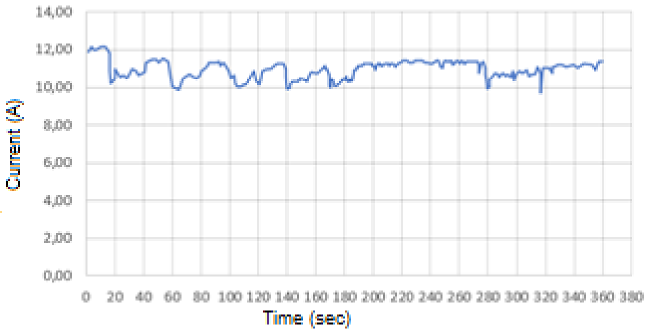

Figure 11. Current-time graph in the 2nd flight of the UAV

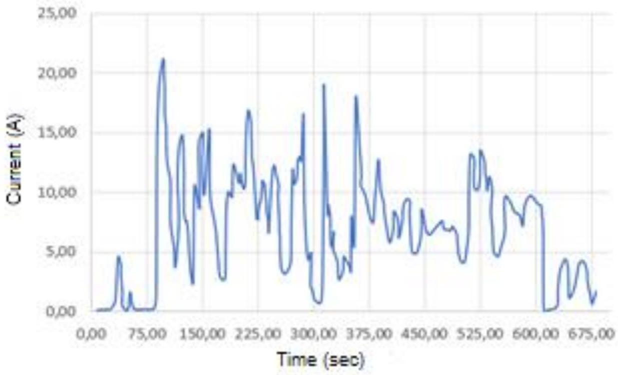

Figure 12. Current-time graph of the 3rd flight of the UAV

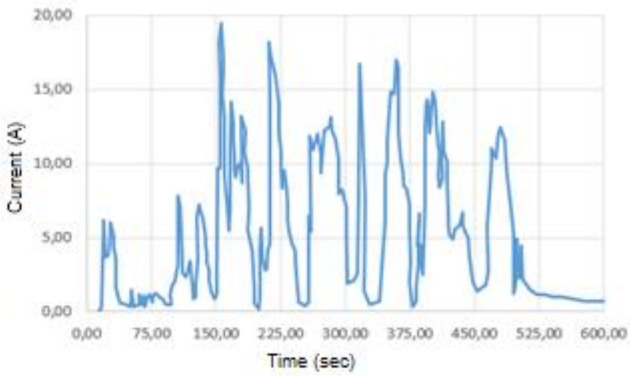

Figure 13. Current-time graph of the 4th flight of the UAV

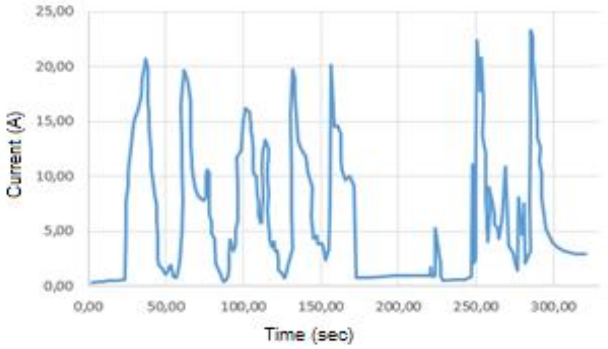

Figure 14. Current-time graph of the 5th flight of the UAV

In Figure 15, Figure 16, Figure 17, Figure 18 and Figure 19, the battery voltage-time graphs taken after five different flights with the UAV are presented. These flights were carried out with a 3S 3300 mAh fully charged battery. The fully charged battery voltage is 12.6 V. Since the battery was under load during the flight, the measured voltage decreased to 10 Volts momentarily.

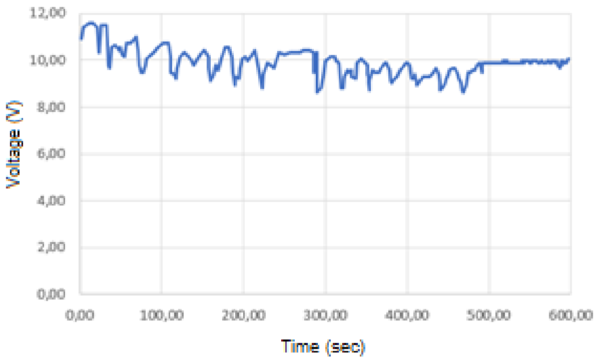

Figure 15. Voltage-time graph of the 1st flight of the UAV

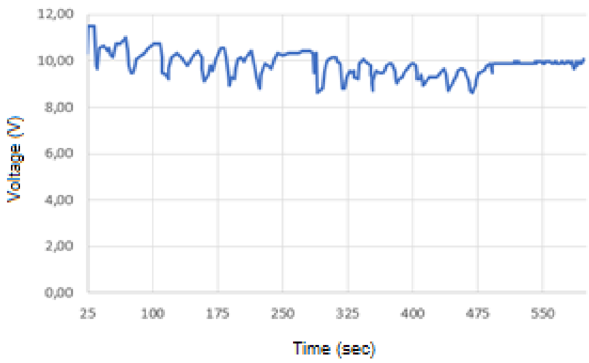

Figure 16. Voltage-time graph in the 2nd flight of the UAV

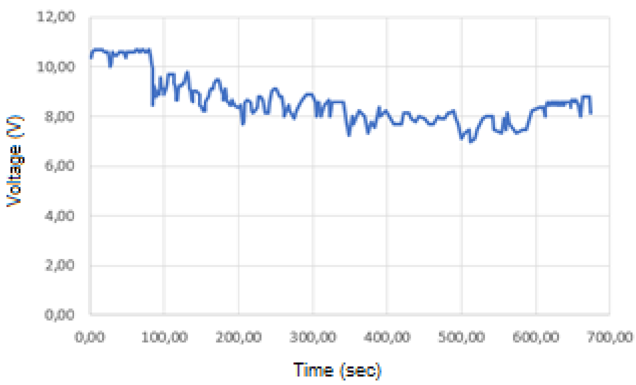

Figure 17. Voltage-time graph of the 3rd flight of the UAV

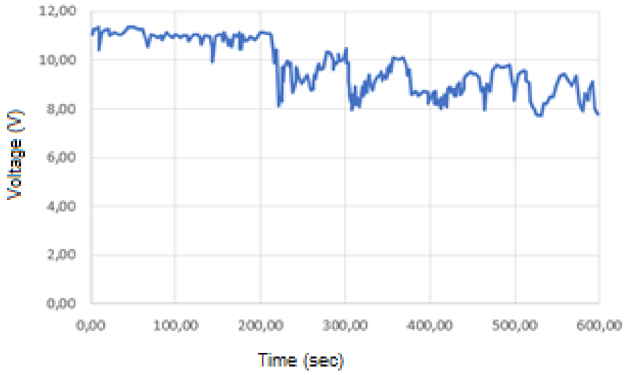

Figure 18. Voltage-time graph of the 4th flight of the UAV

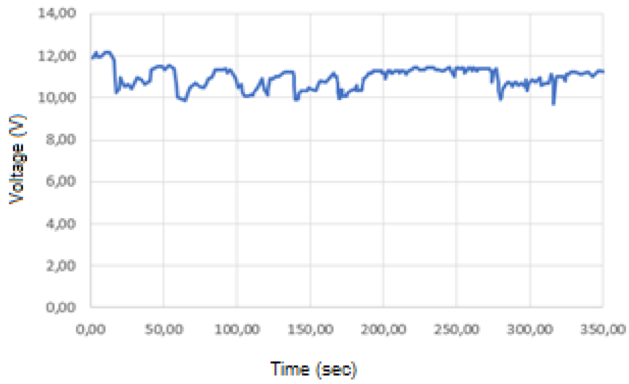

Figure 19. Voltage-time graph of the 5th flight of the UAV

4. Conclusion and Discussion

In this study, it is aimed to obtain the necessary condition monitoring data for the calculation of the remaining useful life of the batteries used in fixed-wing UAVs by using prognostic methods. A total of 4 flights in manual and stabilized modes and 1 flight in autonomous mode were successfully completed with the produced UAV. During the flight, wind-related problems affecting the stability of the UAV were encountered. In long-haul flights, there were breakouts while data was being transferred from the UAV via the telemetry system. During manual, stabilized and autonomous flight, graphs of current drawn from the battery, graphs of voltage drawn from the battery, graphs of flight altitude, discharge graphs of the battery and graphs of the remaining battery percentage were taken from the UAV. As a result of the test flights, useful data was selected for the training of the prognostic software. The selected data has been converted into numerical data in the excel environment. In this way, situation monitoring data to be used in the prognostic software that will be used to calculate the flight time of the UAV in future flights were created. It is anticipated that the data in this study can be used to calculate the flight time of prognostic methods in military and civilian areas. In addition, it is thought that this study will shed light on researchers who will conduct studies on sportive aviation and prognostic methods.

Ethical approval

Not applicable.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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