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Battery Discharge forecast applied in Unmanned Aerial Vehicle

Abstract. *This paper proposes a comparative study methodology for the prediction of Li-Po (Lithium Ion Polymer) batteries discharge in UAVs (Unmanned Aerial Vehicles) using four approaches based on Artificial Neural Networks (ANNs) using Multilayer Perceptron (MLP) and Extreme Learning Machine (ELM) techniques, Polynomial Regression, and Kalman Filter (KF). The information estimates are important to assist in making decisions on which missions can be addressed to UAVs when supplied by such batteries. The data series for the experiments are obtained from tests carried out on a test bench.*

Streszczenie. *W artykule przedstawiono stadium porównawcze metodologii przewidywania procesu rozładowania baterii litowych wykorzystujących sieci neuronowe. Baterie te były stosowane w pojazdach typu dron.* ***Przewidywanie procesu rozładowania baterii w pojazdach typu dron***

Keywords: Artificial Neural Networks; Batteries; Kalman Filter; Polynomial Regression; UAVs.
Słowa kluczowe: sztuczne sieci neuronowe; baterie; Filtr Kalmana; Wielomian regresji; UAV.

Introduction

The use of batteries in UAVs provides some prominent advantages over the use of propellant combustion. Among them, it is worth to mention that weight, noise, and emission are drastically reduced, while improved power control capability also exists [1]. Batteries are energy storage devices that convert chemical energy into electric power, and vice-versa. Batteries are constituted by a pair of electrodes (anode and cathode) immersed in an electrolyte [2].

However, it is very important to monitor the battery state of charge in UAVs. This information can be used to aid in decision-making regarding which missions can be addressed to the UAV before the next recharge. There are many uncertainty factors for the proper monitoring of batteries such as the state of charge, state of health and the discharge curve, which all characterize the battery status.

This work presents a comparative study of techniques for discharge estimation, which are KF, ANNs using MLP and ELM, and Polynomial Regression. All techniques are used to forecast discharge curves of Li-Po batteries. The paper is organized as follows. Section 2 shows how data are collected and a brief description on the experimental setup. Section 3 presents two models for estimation based on ANNs, which are MLP and ELM. Section 4 discusses the polynomial regression method, which is commonly used in temporal estimates. Section 5 describes the KF method, while Section 6 presents the detailed analysis of experimental results. Finally, some remarkable conclusions are given in Section 7.

Database

The UAV used in the experimental tests is model Gyro-200ED-X8 manufactured by Gyrofly, which is composed by eight rotors. It is often used in universities, technical schools and other educational institutions for didactic and research purposes.

The UAV provides open communication with access to telemetry data, all embedded sensors, and hardware that includes a high-level microcontroller so that customized codes can be used. It is also equipped with a 14.8-V, 2-Ah Li-Po battery [3].

Fig.. 1. UAV model Gyro-200ED-X8 by Gyrofly.

The initial stage of the proposed study considers the estimation of the state of charge when the battery current is constant. This case emulates the UAV operation with constant position and height when monitoring a given area. The experimental workbench shown in Fig. 2 was built for this purpose, where the battery is discharged with constant and adjustable current levels.

The electronic load allows adjusting the discharge current up to 2.5 A at intervals of 0.15 A. This device is connected to a computer through a radio frequency link so that the load can be properly controlled while recording data on the battery current and voltage.

The load is divided into two stages i.e. analog and digital. The analog stage includes a closed-loop system composed of an operational amplifier and a MOSFET (metal oxide semiconductor field effect transistor) responsible for discharging the battery. The digital stage consists of a PIC (programmable integrated circuit) microcontroller model 16F877A, which controls the discharge current, records voltage and current data, and performs radio communication with the computer. Figures 3 and 4 show part of the experimental setup.

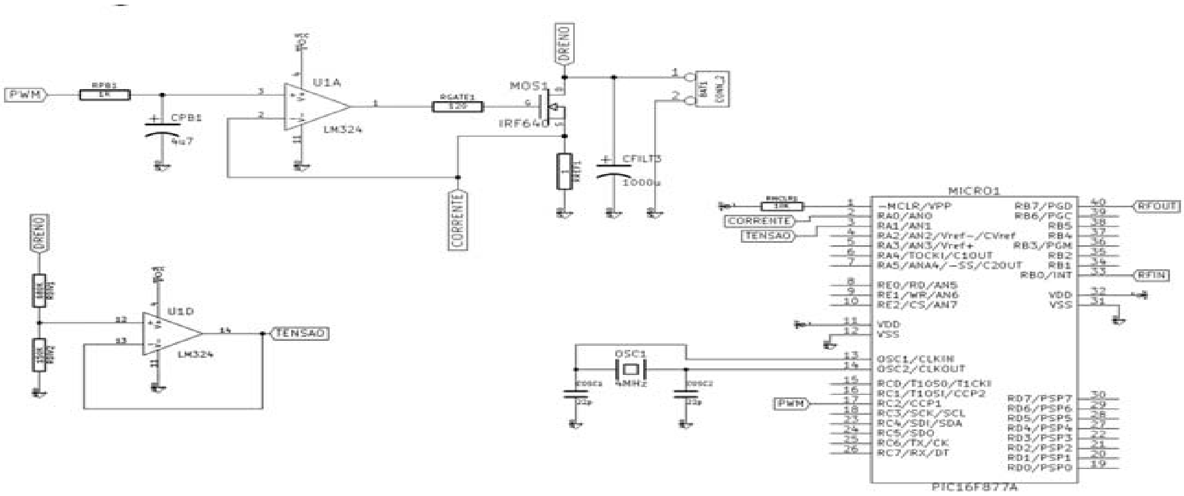

Fig. 2. Schematic representation of the experimental workbench.

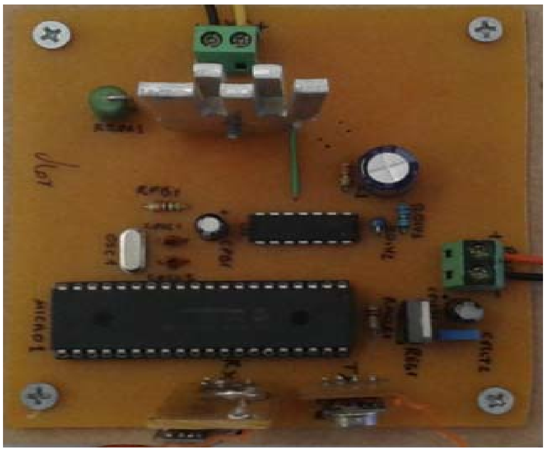

Fig. 3. Electronic load.

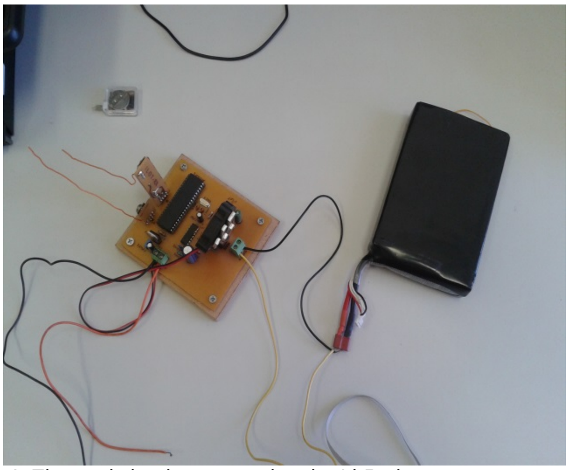

Fig. 4. Electronic load connected to the Li-Po battery.

A supervisory computer software is used as a man-machine interface, which is used to set the discharge current, monitor the real-time quantities in the battery, and generate the proper file containing data for later analysis. A Li-Po battery was used for this purpose, as discharge tests were performed using currents rated at 1.0 A, 1.5 A, 2.0 A, and 2.5 A. The battery was discharged until the voltage across it reached 12.5 V in each test. Voltage data were recorded at a sampling rate of one sample per minute. Fig. 5 shows the data obtained in the tests.

ANN Estimation

Two ANN-based approaches are used in this work, which are MLP and ELM. Since the battery electrochemical processes are inherently complex, this must be considered a nonlinear system, since the relationship between the current and voltage at distinct temperature levels, the state of charge, and the state of health are typically unknown. Estimating the battery behavior is a difficult and challenging task to accomplish.

According to [4], ANNs are inspired by the human brain's ability to learn, being an effective technique to estimate the behavior of batteries. ANN is defined by one or more layers containing neurons with weighted interconnections between them.

a) MLP

MLP is often used in nonlinear estimation [5] by employing the backpropagation algorithm [6]. in order to adjust the proper weights. MLP is implemented in this work based on the original discharge curves presented in Fig. 5, while the MLP structure is represented in Fig. 6.

In order to estimate degradation, a model was implemented based on the aforementioned structure. The network inputs are the sampling times for the voltage, while the desired outputs are the voltages in the original curves. Fig. 7 shows the estimated values during the tests considering that the battery current is 1 A, 1.5 A, 2.0 A, and 2.5 A.

b) ELM

ELM is a neural network approach proposed in [7] employing a simple and efficient learning algorithm. This approach has a single hidden layer generated with random weights and an output layer whose weights are obtained by the least-squares method.

In order to estimate the discharge curves, 10 neurons were employed in the hidden layer. Fig. 8 shows the network architecture and Fig. 9 represents the estimated discharge curves using ELM.

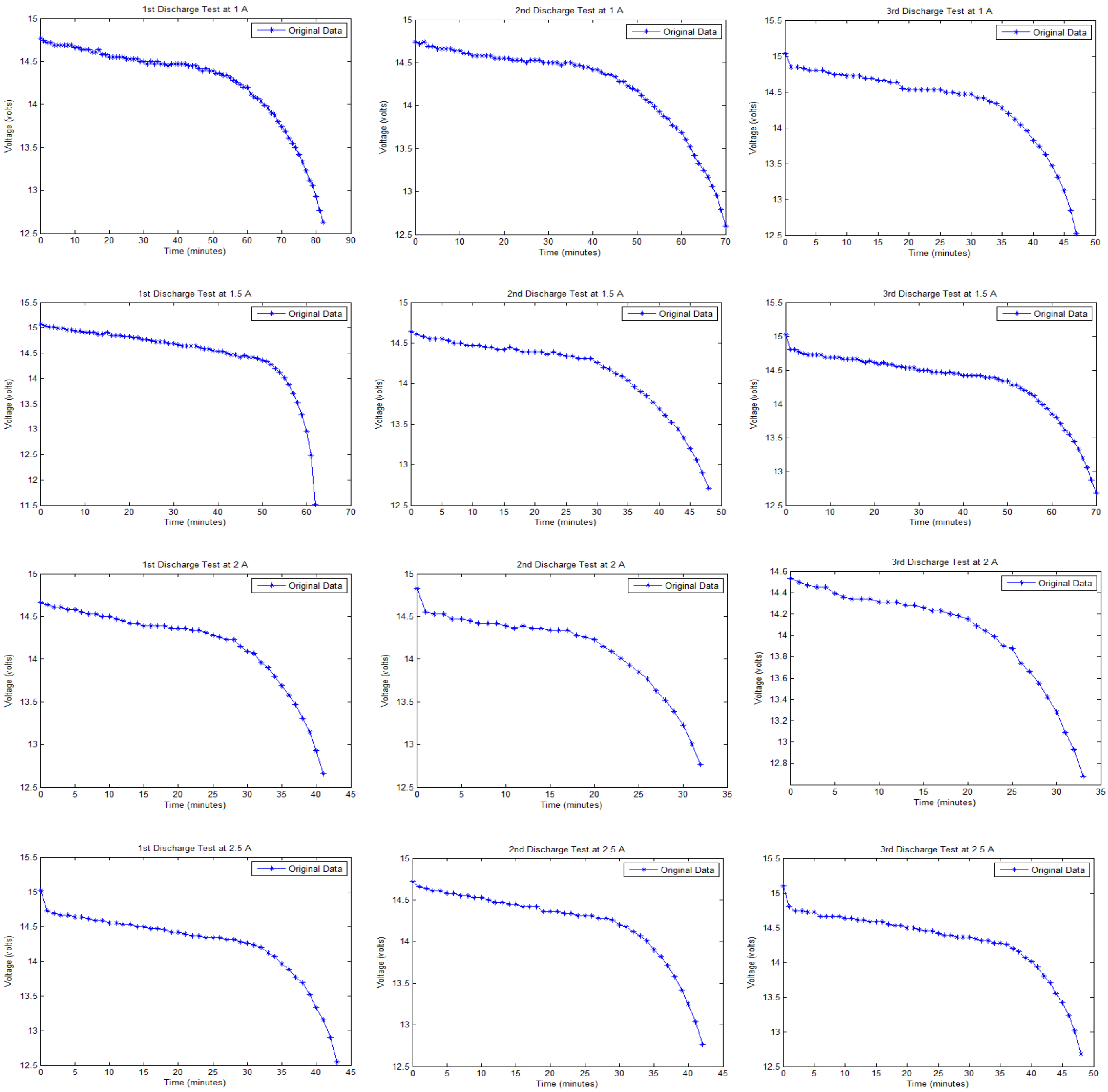

Fig. 5 Results obtained during battery discharge for several values of the battery current.

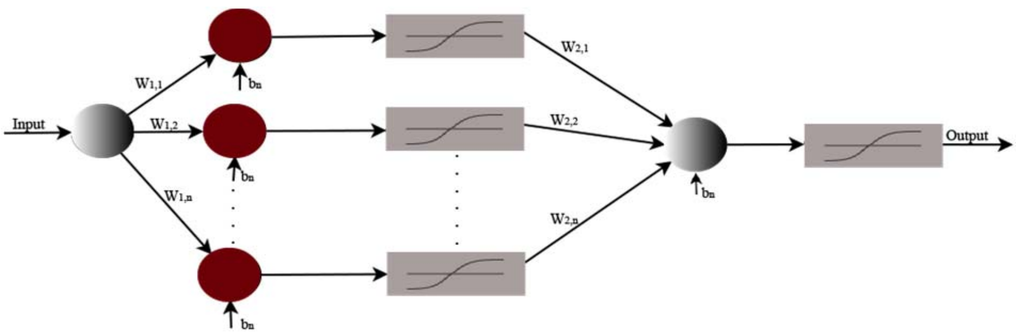

Fig. 6. MLP structure.

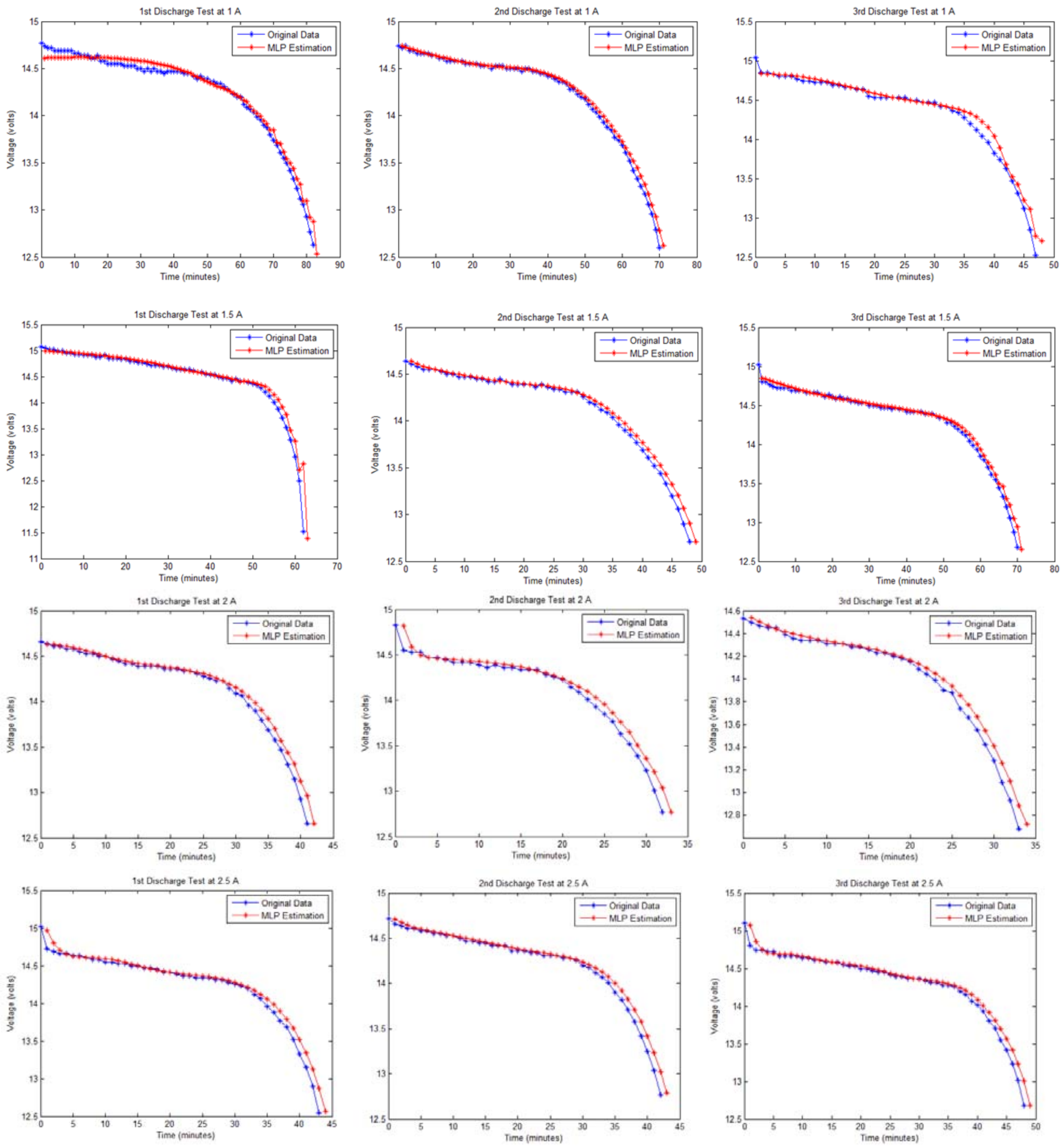

Fig. 7. Comparison between original data and MLP estimation for several values of the battery current.

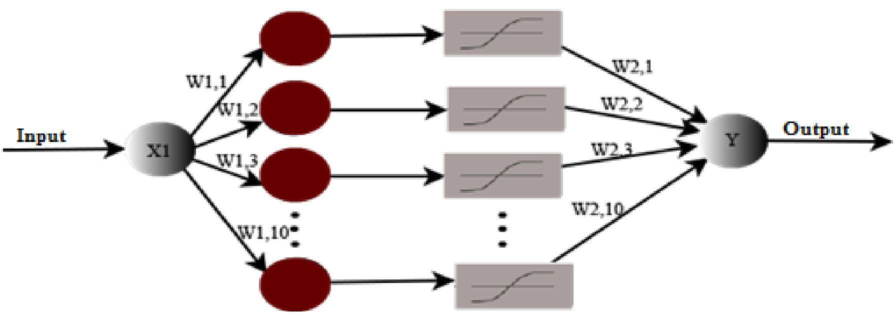

Fig. 8. ELM structure.

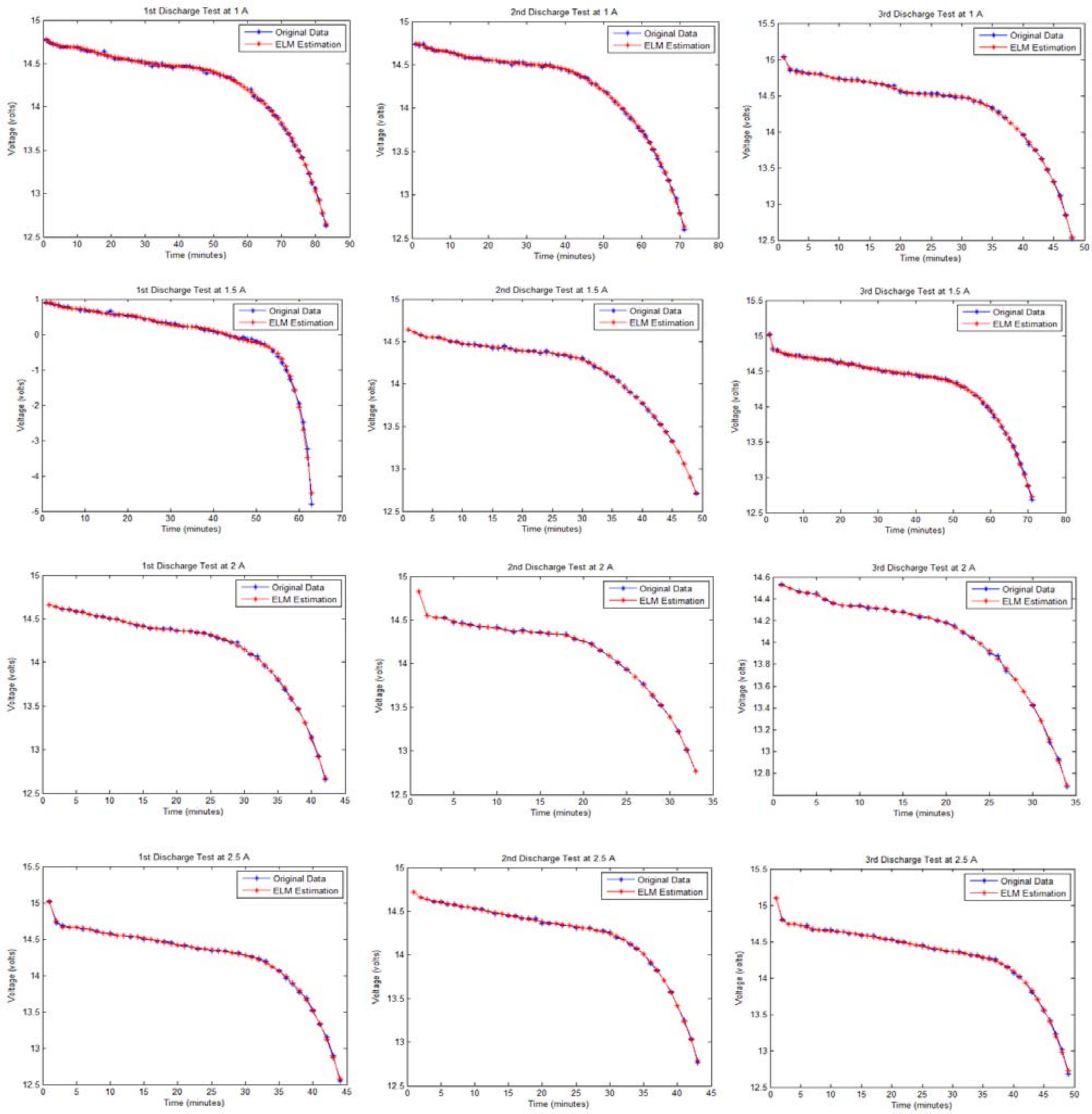

Fig. 9. Comparison between original data and ELM estimation for several values of the battery current.

Polynomial Regression Estimation

The polynomial regression technique is the third method investigated in this work. A polynomial regression is a particular case of the general multiple linear regression [8]. It models the relationship between two variables by setting an equation to the observed data. Expression (1) shows the adjustment function [8]:

$$y = a_0 + a_1 x + a_2 x^2 + \cdots + a_m x^m + \epsilon \quad (1)$$

where $a_0 \ldots a_m$ are the polynomial coefficients; $x \ldots x^m$ are the predicted values for the independent variable, and ϵ is a parameter that aggregates the residual factor and possible measurement errors.

Several polynomials were tested in this work for the best fitting to the original discharge curves. The best choice corresponds to another method called coefficient of determination (R^2), which allows evaluating curve fitting properly and can be calculated according to expression (2).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y(i) - \hat{y}(i))^2}{\sum_{i=1}^{n}(y(i) - \bar{y}(i))^2} \quad (2)$$

where $y(i)$ represents original data; $\hat{y}(i)$ is the estimated value for $y(i)$, and $\bar{y}(i)$ corresponds to the average of the estimated values.

Fig. 10 shows the estimation results when using a 7[th] degree polynomial, which represents the best fitting obtained by the coefficient of determination method.

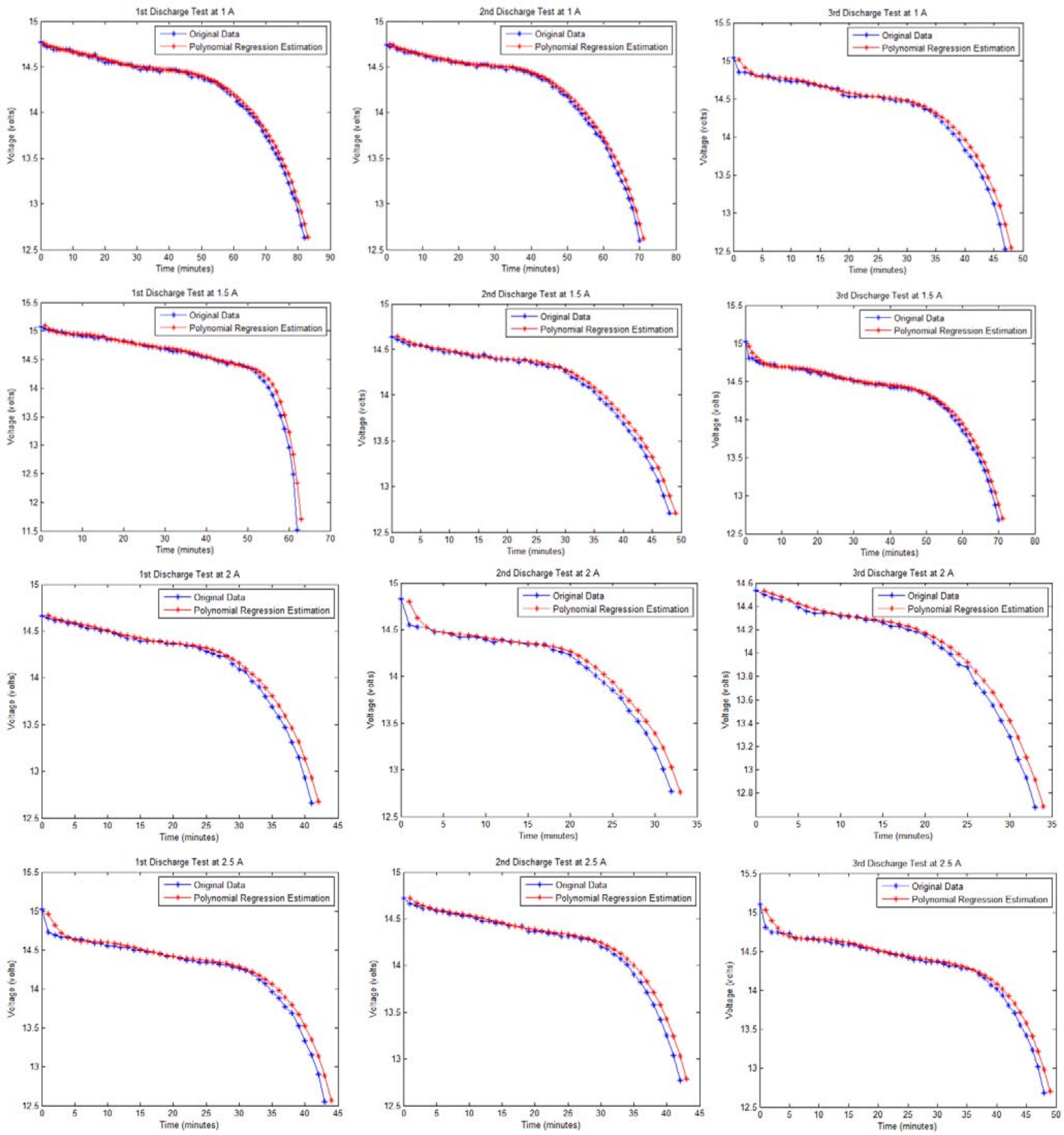

Fig. 10. Comparison between original data and polynomial regression estimation for several values of the battery current.

5. KF Estimation

According to [9]., KF is a method that uses several measurements of random variation (noise) over time in order to estimate the behavior of a robust system over its lifetime. The use of filtering algorithms has become widespread in equipment failure prediction applications as seen in [10, 11]. In order to implement the algorithm, two steps are necessary: prediction (expressions (3) and (4)) and correction (expressions (5), (6), and (7). It is also worth to mention that noises represented by *w* and *v* are not employed in the proposed model.

(3) $$'x_{\bar{k}} = A'x_{k-1} + Bu_k$$

(4) $$P_{\bar{k}} = AP_{k-1} + A^T + Q$$

where *A* is state transition model, which is applied to the previous state 'x_{k-1}; *B* represents the control inputs applied to the input vector u_k; *P* is the variable that contains the covariance error in the previous state; *Q* is the noise covariance, which is a constant value in this case since *w* is neglected in this study.

During the prediction step in (3),the next state is measured, while the next error covariance matrix is designed in (4).

(5) $$K_k = P_{\bar{k}} H^T (H P_{\bar{k}} H^T + R)^{-1}$$

(6) $$'x_k = 'x_k + K_k(z_k - H'x_{\bar{k}})$$

(7) $$P_k = (I - K_k H) P_{\bar{k}}$$

where H is the observation variable that maps the real state space in the observed one; R is observation noise covariance, which is also constant since v is neglected; z_k is the observed value; I é is a constant factor, which is equal to 1 most of the times.

The correction step in(5) deals with the Kalman gain. The estimate is updated in (6) using measurement z_k, which corresponds to the battery voltage. The error covariance is updated in (7). Figure 11 shows the estimation results when using KF.

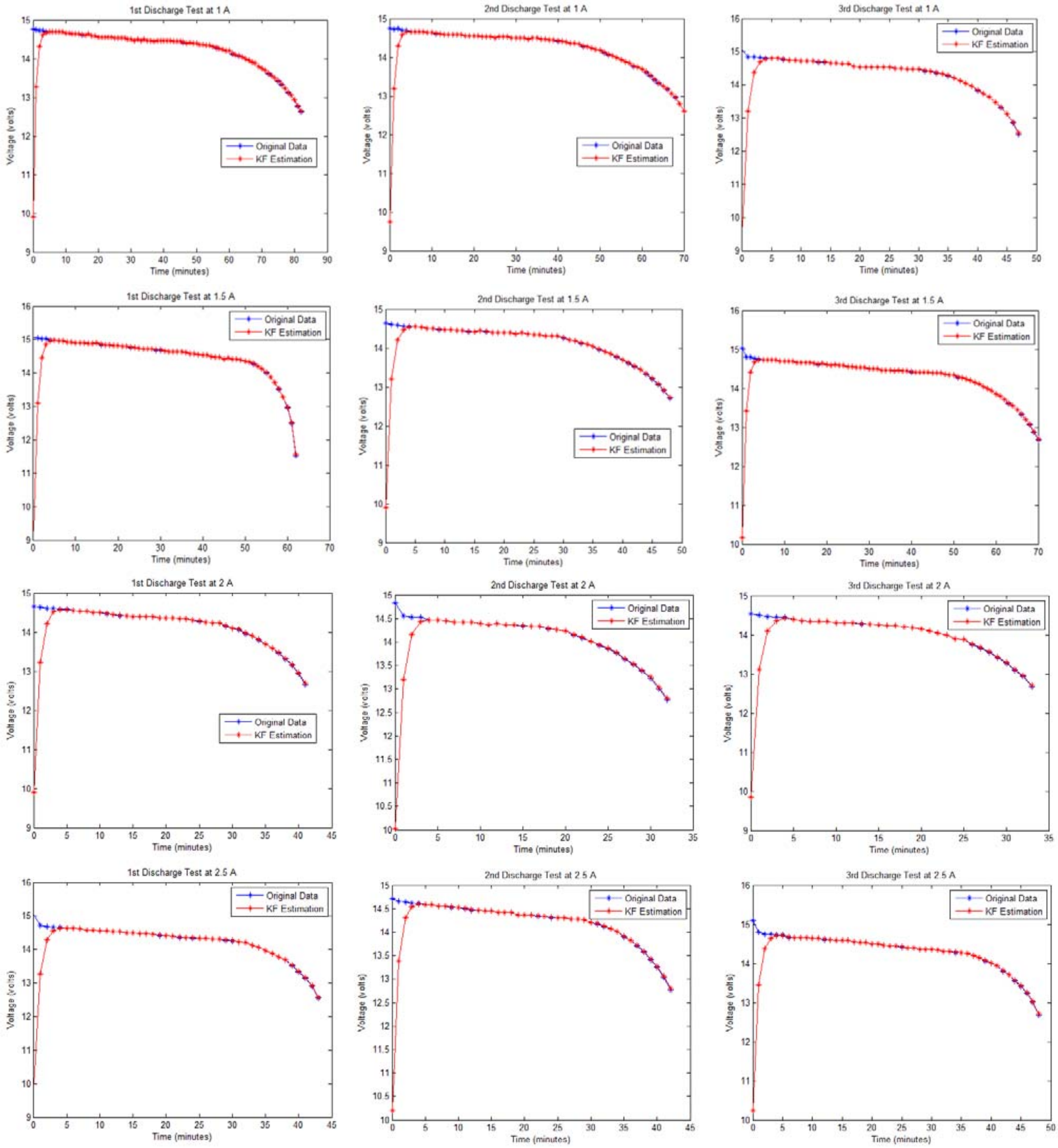

Figure 11. Comparison between original data and KF estimation for several values of the battery current.

Results and Discussion

Table 1 presents a comparative analysis for the highest value of R^2 obtained by the methods investigated in this work. It is worth to mention that all approaches have provided a coefficient of determination higher than 0.90.

It can be seen that satisfactory results are then obtained according to Table 1, which also shows that the best performance is achieved by using KF, although small differences exist when compared to the other methods. For instance, the 9th test estimation is 0.9993 when using MLP or Polynomial Regression. On the other hand, the values obtained when using ELM and KF are 0.9995 and 0.9999, respectively. Therefore it can be stated that KF is the most efficient approach for the estimation of discharge curves regarding Li-Po batteries if compared with the remaining studied methods.

Table 1. Comparison among the coefficients of determination for the estimation methods.

Tests	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th
MLP	0.9982	0.9993	0.9986	0.9956	0.9994	0.9987	0.9995	0.9987	0.9993	0.9978	0.9994	0.9986
ELM	0.9993	0.9993	0.9992	0.9960	0.9995	0.9993	0.9995	0.9995	0.9995	0.9995	0.9995	0.9994
7th-Degree Polynomial Regression	0.9993	0.9993	0.9985	0.9956	0.9994	0.9986	0.9995	0.9983	0.9993	0.9978	0.9994	0.9974
Kalman Filter	0.9997	0.9997	0.9997	0.9995	0.9995	0.9997	0.9999	0.9998	0.9999	0.9998	0.9999	0.9999

Conclusions

This paper has described four methods for the estimation of discharge curves in a Li-Po battery used in UAVs. MLP, ELM, polynomial regression, and KF have been properly investigated, while an exponential model for the evolution of the degradation has also been introduced. In order to estimate the curves when using the aforementioned methods, the time instants for the voltage samples are the inputs, while the outputs correspond to the voltage values and the reference is represented by the current level. Data were then recorded using an experimental setup, where Li-Po batteries used in UAV model Gyro-200ED-X8 were evaluated. The performed tests represent the steady flight condition of the UAV. Good results have been obtained when using the aforementioned models, even though they are simple approaches. The best results could be obtained when using KF, although the remaining methods also have presented satisfactory performance, thus validating the proposed study. Future work includes the estimation of other uncertainties e.g. the battery state of charge, which is also an important parameter regarding the battery status.

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