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SYLLOGISM OF Li-$FePO_4$ BATTERY CELL VOLTAGE PARAMETER GUESS UNDER APERIODIC DYNAMIC CURRENT PROFILE BY SOME DATA-DRIVEN TECHNIQUES: A ERROR-BASED STATISTICAL COMPARISON BETWEEN DECISION TREE, SUPPORT VECTOR, BEE COLONY, AND NEURAL NETWORK

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Abstract: The various procedures are used in the literature for defining battery parameter change such as direct measurement methods, model-based methods, and data-driven methods, which contain the algorithms used in this paper also. The main aim of this study is to present a powerful and highly correct way of parameter forecasting of the A123 Systems 26650 cylindrical type Li-FePO4 battery cell. A few of the goal of this paper is to show the guessing performance of the artificial bee colony algorithm, which has a very limited number of applications on the battery parameter of literature, under the non-periodic dynamic charge/ discharge current profile. Then, a comparison has been made between artificial bee colony, artificial neural networks, support vector machine, and decision tree algorithms used in the paper. The load-connected terminal voltage is defined by considering the 100%-60% state of charge range in the primary usage areas of the batteries. A statistical comparison has been made by considering the absolute errors, squared errors, and the regression values information regarding the results presented by the methods. Consequently, the regression values that give information about the consistency of the confidence interval and results, of the bee colony, neural network, support vector, and decision tree methods have been determined as 99.92%, 99.75%, 96.00% and 95.79%, respectively. Moreover, mean squared errors of the methods has been calculated as 0.00202%, 0.00648%, 0.00998%, and 0.11%, respectively. As a new generation algorithm, artificial bee colony, which gave the most successful results according to the results obtained in the study, has been compared with two different methods selected from the existing literature, eXtreme Gradient Boosting and Smoothed eXtreme Gradient Boosting.

Keywords: Artificial intelligence, Battery, Machine learning, Parameter, Forecasting

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1. Introduction

A suitable battery management system (BMS) is needed for good management of battery blocks in electronic systems. For increasing the performance and control capability of BMSs, the correct algorithm has to be running. In order for BMSs to step in at the right time and interfere with system, it is important to determine parameters such as battery current (I), open circuit voltage (V_{oc}), terminal voltage (V_T), state of charge (SoC), number of cycles (N_c), and state of health (SoH) with consistent accuracy. There are many different methods that have been tried on Li-Ion batteries in the literature. There are different traditional approaches such as Coulomb counting, electrical equivalent circuit models, and mathematical or electrochemical models for the detection of V_T, which is the subject of this study and is highly dependent on the SoC. The development of data science (DS) necessarily incorporates machine learning (ML) and artificial intelligence (AI) techniques into applications in the field of parameter estimation of Li-Ion batteries. ML models allow researchers to extract patterns and trends from data and enable them to generalize the finding to the novel data with affordable computations. However, the number of studies conducted with the algorithms that are the subject of this study is either very limited or non-existent. Therefore, it is clear that this paper will contribute to the literature to increase the number of sources.

Chemali et al. (2018), have investigated SoC estimation by using artificial neural networks (ANN) to develop BMSs used in Li-Ion batteries. Ipek et al. (2019), have studied SoC estimation for Li-$FePO_4$ batteries by using support vector machine (SVM) and DT-based eXtreme Gradient Boosting (XGBoost). Wang et al. (2019), have used support vector regression (SVR) optimized by artificial bee colony (ABC) to determine the lifetime of Li-Ion batteries. Gradient boosted decision trees (DT) are trained for *SoH* estimation in Khaleghi et al. (2020)'s studies. Huotari et al. (2021), have carried out studies on Li-Ion batteries for enhancing the operating performance of electric forklifts. A good battery design has been tried to be achieved by using *SoH* and N_c estimation. At this stage, autoregressive integrated modeling average (ARIMA) and supervised learning (bagging with decision tree as the base estimator; BAG) has been used. Shu et al. (2021), have conducted a review study including many ML-based methods to determine the *SoH* of Li-Ion battery and to make estimations. Ipek and Yilmaz (2021), have studied *SoC* estimation using XGBoost and hybrid XGBoost under dynamic operating conditions. Carkit et al. (2022), have made parameter estimation under the combined variable charge/discharge profile using decision tree algorithm and artificial bee colony algorithm. Niri et al. (2022), has used AI technology to develop electrodes during the production of Li-Ion batteries. Correlation has been made between production parameters and electrode quality. ML models have been developed to measure the predictability of electrode and cell properties. Yan et al. (2022), have used empirical model and exponential model powered with ABC to find the usable current capacity that varies depending on N_c in Li-Ion batteries. Carkit et al. (2022), have defined V_{oc} and V_T as the *SoC* dependent function by using the electrical equivalent circuit model. Also, particle swarm optimization (PSO), genetic algorithm (GA), and ABC methods have been used in the study. It has been determined that ABC performs successfully according to PSO and GA. Tian et al. (2022), have developed a hybrid model based on convolutional neural network (CNN)-bidirectional long short-term memory (BiLSTM) and attention mechanism (AM) for forecasting the *SoH* of Li-Ion batteries. The available current capacity is monitored for parameter estimation tracking. The root mean square error (RMSE) value has been calculated as less than 0.01. Wei et al. (2023), have researched to predict *SoH* and remaining useful life of Li-Ion batteries using graph convolutional network (GCN) with dual attention mechanisms. The proposed method has accurately predicted the state-of-health and remaining useful life with a minimum root-mean-squared-error of 0.0104 and 5.80, respectively.

This study contributes to the data-driven approaches by using DT, fine Gaussian (FG)-SVM, ANN, and ABC to predict *SoC* and V_T.

2. Materials and Methods

Current technological progress has increased the popularity of data-driven methods, which are based on interpretation by reading data in the direction of traditional forecasting methods. The advantages of these methods include the complexity of the process in traditional methods, and the prevention of possible user errors that have the potential to occur in electrical circuits. On the other hand, these current methods are mainly carried out by software and algorithms (Huotari et al., 2021). Moreover, it needs real test results from experimental data (Wu et al., 2016).

2.1. Decision Tree Algorithm

Decision tree algorithm is a method often used in classification processes in DS and ML. Clustering and prediction processes can be included among the other application areas of the algorithm in the literature. The operation of this algorithm that is given Figure 1, is based on the tree structure (Timucin et al., 2019). In the structure of decision trees, there are leaves at the far end (Han et al., 2000), branches extending from the leaves to the nodes, and the main trunk extending from the nodes where the branches meet to the roots. The algorithm reaches the conclusion point by determining its own path according to the "Ok" or "Not-Ok" answers given to the conditions at the node points. The information sent to the algorithm is divided into smaller pieces and used to reach the final goal (Yang et al., 2013). While doing this, many nodes are determined by the algorithm as in Figure 1, which consists of control conditions. The first node in the structure of the data tree is called the "root node".

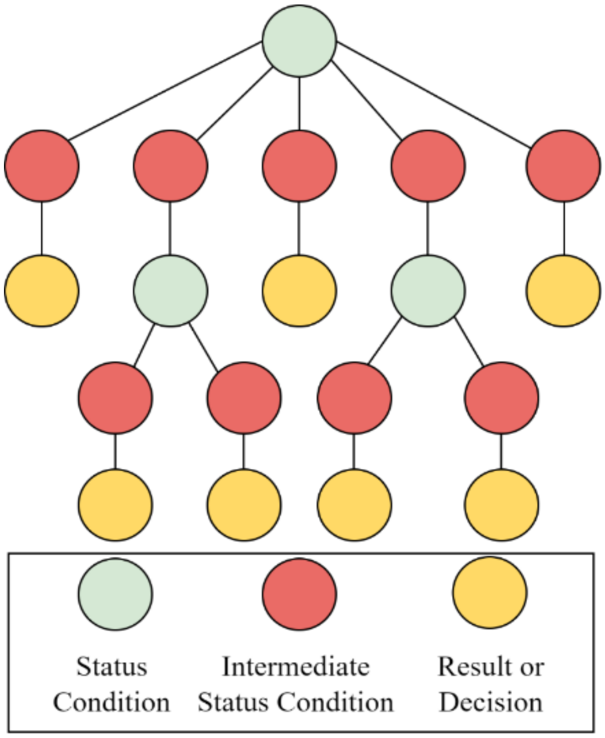

Figure 1. The search structure of DT.

2.2. Support Vector Machine

The basis of SVM is placing the farthest boundary line from the data between two statistically separated data groups and creating the critical territory. For this study, one of the data sets consists of real test results, and the other is the results predicted by SVM. As it can be seen in Figure 2, in determining the final boundary zone, the support vectors (SV) are assisted by the observations closest to the boundary (Panarese, 2022). Here, w_n

represents the internal weights, x_n is the input data, b represents the threshold values, and f is the objective function. The purpose of SVM is to first collect the estimation points in the margin area and align them on f. SVM not only provides relatively accurate prediction results in case of fewer data samples, but also compensates for the shortcoming that the ANN model easily falls to the optimal local extremity (Yao et al., 2021).

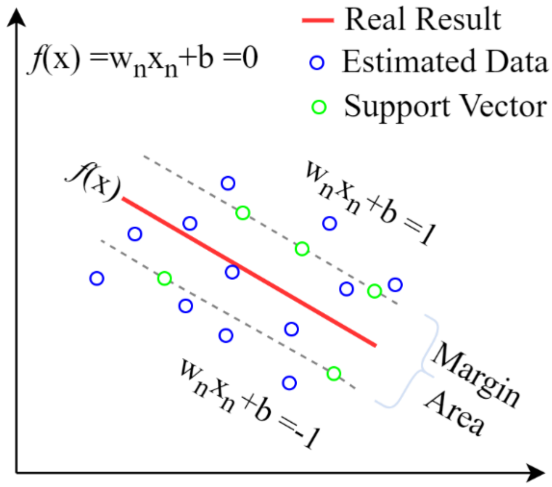

Figure 2. The search structure of SVM.

2.3. Artificial Neural Network

ANN, inspired by the functioning of human brain nerve cells, is accepted as a "black box" model, just like the biological features of the brain (Han et al., 2019). The mathematical and neural model of an ANN is given in Figure 3. In the figure, x_i's represent the input data, w_i values are the ANN internal system weights, f is the activation function, and b is the threshold value. As seen in Figure 4, ANN has at least three layers as input, hidden, and output layers. Data alerts coming from outside are processed through each layer. The processed data reaches the output layer and is transferred to the user by the algorithm. According to the problem for which a solution is sought, a multi-layered method can be obtained by increasing the number of ANN layers by the researchers. In addition to being used as an AI method in some studies, ANN, which is included as an ML method in other some studies, is easy to simulate and non-linear, creating a wide variety of usage areas. Moreover, the use of ANN in battery management applications by different researchers in previous years supports the experience of this method (Wang et al., 2016).

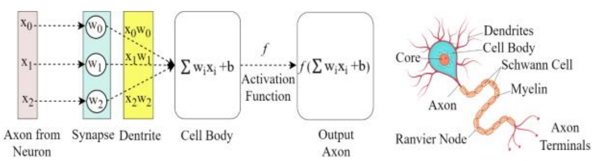

Figure 3. Mathematical model of ANN and exemplary neuron structure.

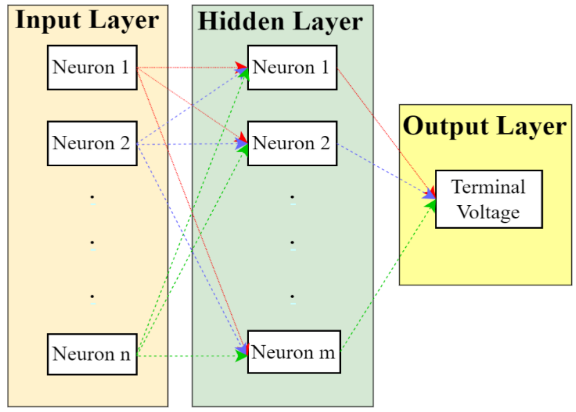

Figure 4. Layer structure and neuron connections of ANN.

2.4. Artificial Bee Colony Algorithm

Another method used in the study is the ABC algorithm. ABC, which is among the AI algorithms, is a current optimization method. In ABC, the basic structure of which is given in Figure 5, bees are divided into three classes: Scout bee, onlooker bee, worker bee (Karaboga et al., 2007). In ABC, scout bees approaching food sources randomly calculate the amount of food in the sources. Afterwards, the worker and onlooker bees are informed by the scout bees and the workflow of directing the bees to the sources begins. Solutions to the problem under study represent the locations of food sources for ABC. The amount of nutrients in food sources corresponds to the suitability (quality) of the solutions offered to the problem (Dogan, 2011). In the decision-making process in ABC, there are traces of the collective decision-making approach used by the bees in natural life in their daily operations (Karaboga, 2014).

3. Results and Discussion

3.1. Parameter Forecasting Using Algorithms

The variation of the cell voltage of the A123 Systems 26650 Li-FePO$_4$ 2500 mAh battery cell, which is the subject of this study, between 100% and 60% *SoC* that has been obtained by ampere-hour (A.h) method, as seen in Figure 6, is examined.

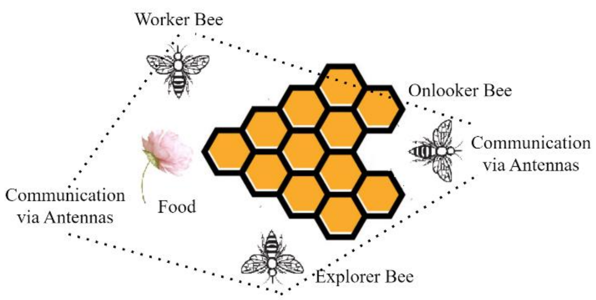

Figure 5. The search structure and communication status of ABC.

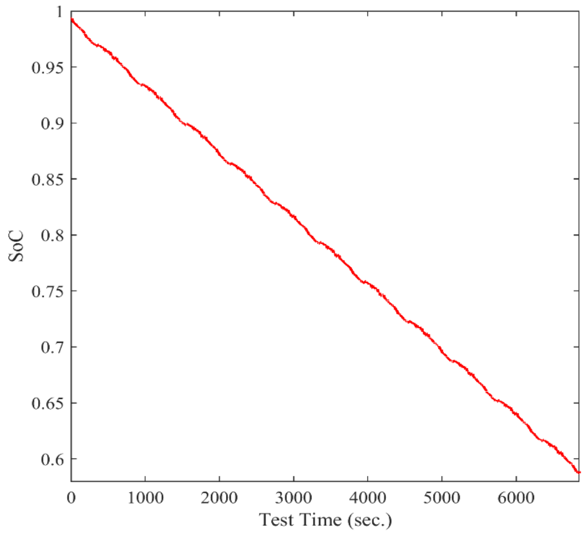

Figure 6. Variation of *SoC* according to current profile.

3.2. Parameter Forecasting Using Algorithms

The variation of the cell voltage of the A123 Systems 26650 Li-FePO$_4$ 2500 mAh battery cell, which is the subject of this study, between 100% and 60% *SoC* that has been obtained by ampere-hour (A.h) method, as seen in Figure 6, is examined. It is aimed to accurately determine the cell voltage in Figure 7 by using the experimental test data of the CALCE Battery Research Group (CALCE, 2022). For increasing the complexity and difficulty level of the study, the preferred voltage and current flow profiles are not periodic as seen in Figure 7 and Figure 8. Moreover, the details of non-predetermined dynamic profiles can be found in Figure 7 and Figure 8. At the stage of determining the V_T, the equation depending on the *SoC* given in equation 1 is used. In the equation, the V_T is defined as the third order exponential function of *SoC*. $a_{1...5}$ represents the coefficients of the equation.

$$V_{T(SoC)}=a_1+a_2(SoC)^3+a_3(SoC)^2+a_4(SoC)^1+a_5 \tag{1}$$

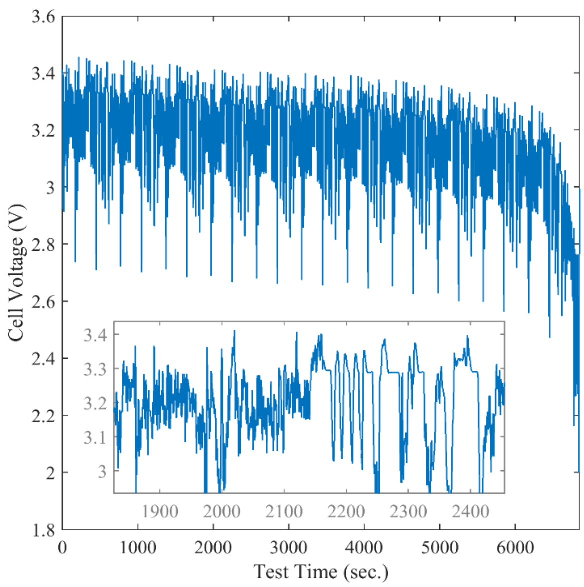

Figure 7. Changing of V_T according to current profile.

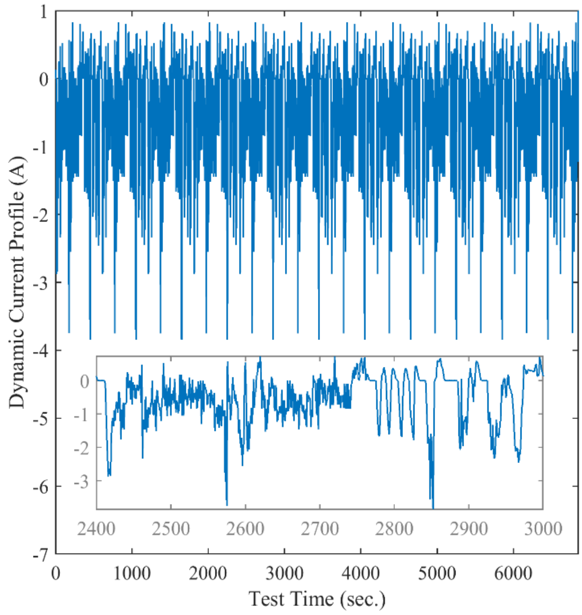

Figure 8. Dynamic current profile.

The branching of the DT algorithm, which is preferred for ML purposes, according to the way it uses the data is given in Figure 9. Final data points are reached by considering V_T, *SoC*, *I*, and test step time information. Although the speed is very high on the server where the data is processed during the operation of the DT, memory and performance requirements occur. The compatibility of the cell voltage generated using the DT algorithm with the real data is given in Figure 10. The absolute error (e_a) and the squared errors (*SE*) obtained according to the information provided by DT are given in Figure 11. During the execution of FG-SVM for prediction, the processing speed is high. On the other hand, the memory and performance requirement is similar to DT. The correspondence of the cell voltage produced using FG-SVM with the actual data is given in Figure 12. The e_a and *SE* obtained according to the information provided by FG-SVM are given in Figure 13.

The processing speed of ANN, which is one of the AI algorithms, is high during its operation for prediction purposes. Levenberg-Marquardt algorithm with 30 neurons selected from the ANN using previous experiences has a high speed (Carkit, 2022). Moreover, the memory and performance requirement are similar to DT and FG-SVM. The correspondence of the cell voltage generated using the ANN with the actual data is given in Figure 14. The e_a and *SE* obtained according to the information provided by ANN are given in Figure 15. Although the speed of the ABC algorithm used in the AI field is high in the server where the data is processed, it is slower than DT, FG-SVM, and ANN. On the other hand, the memory and performance requirement is less than the others. Compatibility of the cell voltage generated using the ABC algorithm with the real data is given in Figure 16. The error information obtained according to the information provided by ABC is given in Figure 17.

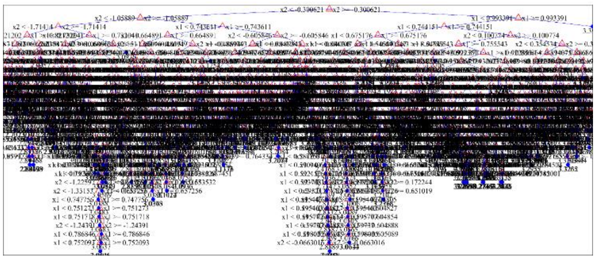

Figure 9. The decision-making strategy of DT.

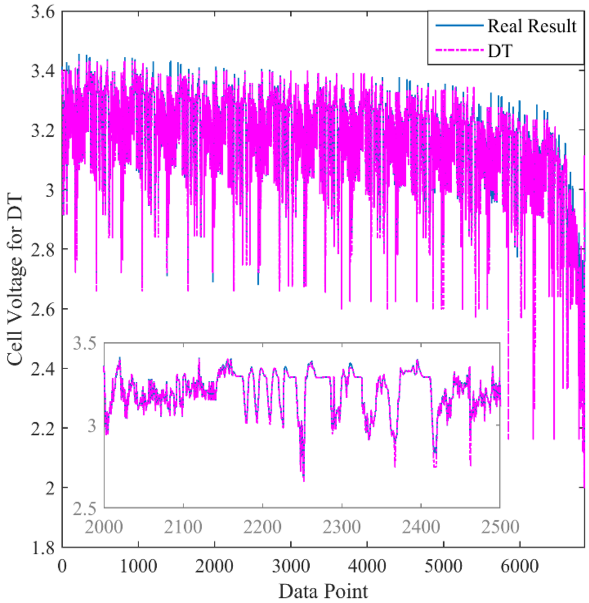

Figure 10. Compatibility of V_T prediction value presented by DT.

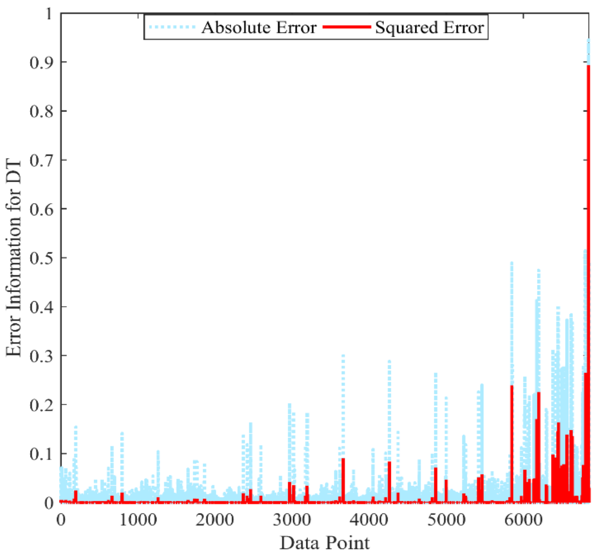

Figure 11. Error information of DT's forecast performance.

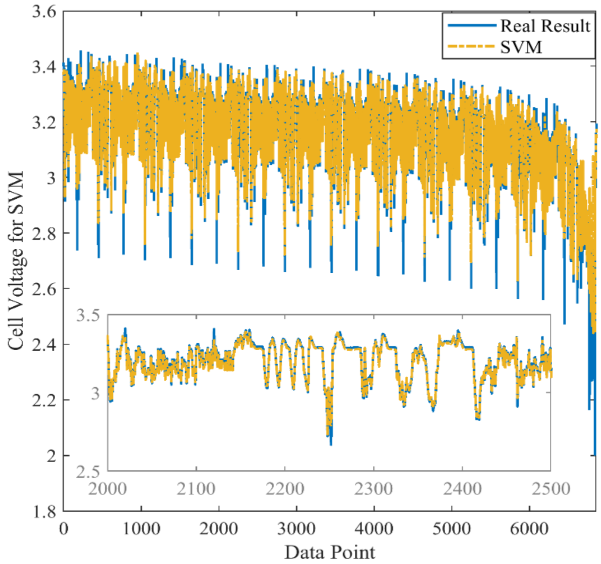

Figure 12. The fit of the V_T prediction value presented by FG-SVM.

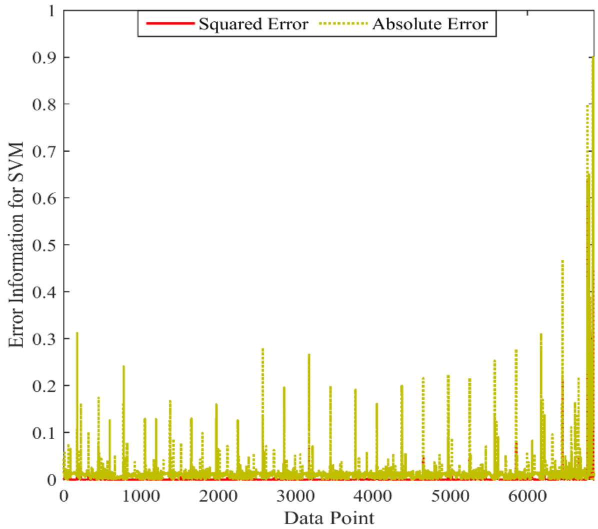

Figure 13. Error information of FG-SVM's forecast performance.

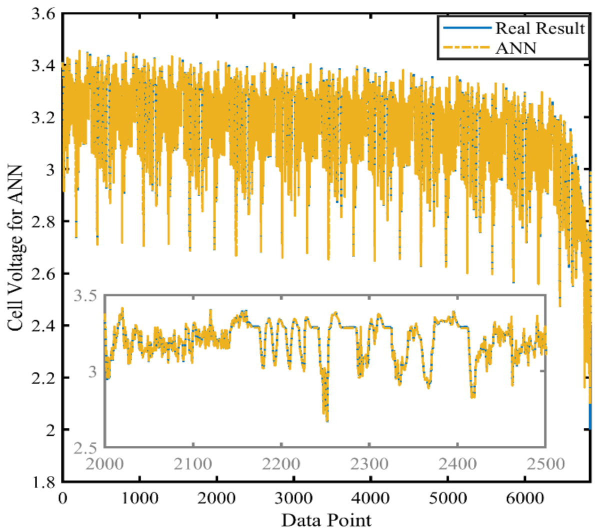

Figure 14. The fit of the V_T prediction value presented by ANN.

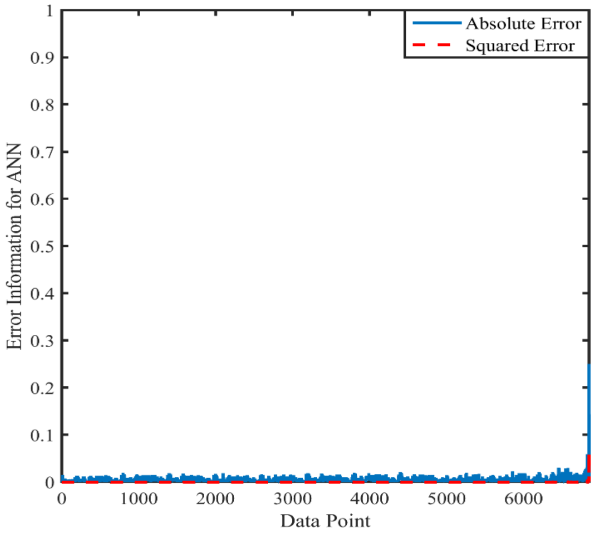

Figure 15. Error information of ANN's forecast performance.

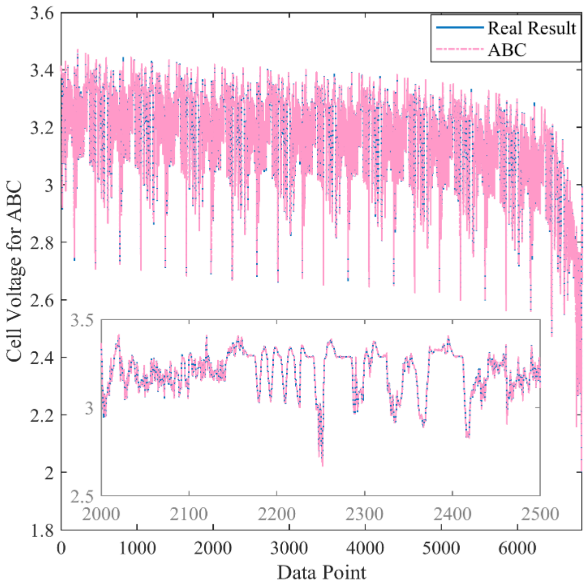

Figure 16. The fit of the V_T prediction value presented by ABC.

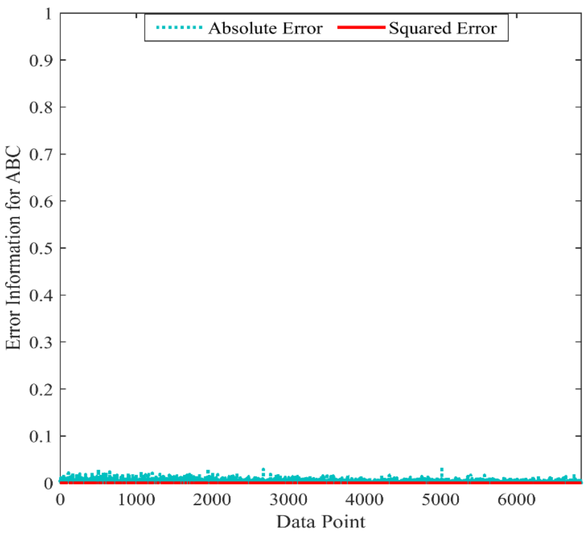

Figure 17. Error information of ABC's forecast performance.

In Table 1, which constitutes the summary theme of the study, error information of methods is given. As can be seen from the table; DT, ABC, ANN, and FG-SVM algorithms have performed with 0.010, 0.003, 0.005 and .012 average e_a respectively. Considering the average e_a, ABC has the most successful method compared to the others. Moreover, the performance of the methods for *MSE* is 0.001, $(2.028)10^{-5}$, $(6.4891)10^{-5}$, and $(9.989)10^{-4}$ respectively. In summary, ABC has outperformed the others methods which are analyzed for this paper in terms of *MSE* and mean e_a. On the other hand, considering the R^2 values given in Table 2. The R^2 values for the DT, ABC, ANN, and FG-SVM algorithms are 0.9579, 0.9992, 0.9975, and 0.9600 respectively. Considering the R^2 statistical evaluation method, the most successful method is seen as ABC. When the results are evaluated in the context of the literature, the methods used provide the correct interpretation of the research. In addition, the results obtained are consistent with the literature results. The data showing the comparison of the study with a similar study in the literature are given in Table 2. R^2 values of ABC, ANN, Smoothed XGBoost, and XGBoost methods have been obtained as 99.92%, 99.75%, 99.43%, and 98.81 respectively. The *MSE%* values of ABC, ANN, Smoothed XGBoost, and XGBoost methods have been determined as $(2.02)10^{-3}$, $(6.48)10^{-3}$, $(20)10^{-3}$, and $(50)10^{-3}$ respectively. As can be seen, ANN and ABC methods have outperformed XGBoost and Smoothed XGBoost that are similar methods in the literature. Even, the ABC method has given more accomplished results than all the literature methods which have been given in this study.

Table 1. Error statistics of algorithm outputs

Algorithms	DT	ABC	ANN	FG-SVM
Min (e_a)	0	$(7.851)10^{-8}$	$(5.929)10^{-7}$	$(9.316)10^{-6}$
Max (e_a)	0.945	0.034	0.250	0.900
Mean (e_a)	0.010	0.003	0.005	0.012
Min (SE)	0	$(6.164)10^{-15}$	$(3.516)10^{-13}$	$(8.679)10^{-11}$
Max (SE)	0.893	0.001	0.062	0.811
MSE	0.001	$(2.028)10^{-5}$	$(6.4891)10^{-5}$	$(9.989)10^{-4}$

Table 2. Achievement comparison of performed forecast techniques against dynamic I-V profile

Methods	Reference	R^2 (%)	MSE (%)
DT	This study	95.79	(0.11)
ABC		99.92	$(2.02)10^{-3}$
ANN		99.75	$(6.48)10^{-3}$
FG-SVM		96.00	$(99.8)10^{-3}$
XGBoost	(Ipek et al., 2021)	98.81	$(50)10^{-3}$
Smoothed XGBoost		99.43	$(20)10^{-3}$

4. Conclusion

In this study, which is planned by using up-to-date methods such as artificial intelligence and machine learning; firstly, knowledge about decision tree algorithm, support vector machine, artificial neural network, and artificial bee colony algorithm are given. The change of cell voltage and state of charge with the effect of dynamically showing current profile has been investigated. Estimation data of cell voltage have been obtained by running the algorithms. It is seen that the decision tree algorithm, which is generally used in classification processes in data mining, could have used in the parameter estimation of batteries with acceptable accuracy in this study. The support vector machine method, which is frequently used in regression processes by using support vectors, has presented more acceptable results than the decision tree in terms of mean squared error and R squared. The artificial neural network method, which has been increasingly used in recent years, has shown more successful results than machine learning methods and reference two methods in the literature. As a result of the comparison of each method that have been studied in paper, it has been determined that the artificial bee colony algorithm has showed a more successful prediction performance. On the other hand, it has been seen that the artificial intelligence algorithms have been slower than the machine learning algorithms. It has been noticed that the artificial intelligence algorithms have need less memory and performance support. Furthermore, it has been determined that artificial bee colony and artificial neural network have given more successful results than two different methods which have been chosen from the current reference studies in the literature.

Author Contributions

The percentage of the author(s) contributions is present below. All authors reviewed and approved final version of the manuscript.

	T.Ç.	S.Ç
C	50	50
D	50	50
S	50	50
DCP	50	50
DAI	50	50
L	50	50
W	50	50
CR	50	50
SR	50	50

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision.

Conflict of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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