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ESTIMATION OF ELECTRIC VEHICLE MULTIPLE PACKAGE LITHIUM-ION BATTERY STATE OF CHARGE USING AN EXTENDED MACHINE LEARNING

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Abstract: The estimation of battery state-of-charge (SOC) in electric or hybrid vehicle has vital importance in the designing process of battery management systems. The state-of-charge estimation is implemented using different modelling approaches, model-based estimators such as Kalman filtering and Luenberger observer and data-driven based modelling techniques like artificial neural network and machine learning methods. This study aimed to develop a battery state-of-charge estimation method and proposed a novel architecture for multiple battery back SOC estimation using an extended learning machine (ELM). The ELM approach is applied considering battery operating conditions using global vehicle driving profiles, New European Driving Cycle and Worldwide harmonized Light vehicles Test Procedure. The performance of the proposed SOC estimation method is evaluated by using statistical criteria (RMSE, R2, MAPE). Consequently, the obtained results show that a data-driven ELM approach with a less complex structure can obtain better performance compared with other advanced estimator methods under different operating conditions.

Keywords: Extended machine learning, State of Charge, Estimation, Lithium-ion, Battery

Elektrikli Araçların Çoklu Paket Lityum-İyon Batarya Şarj Durumunu Genişletilmiş Bir Makine Öğrenmesi Kullanarak Tahmini

Öz: Elektrikli veya hibrit araçlarda batarya şarj durumunun (SOC) tahmini, batarya yönetim sistemlerinin tasarım sürecinde hayati öneme sahiptir. Şarj durumu tahmini, farklı modelleme yaklaşımları, Kalman filtreleme ve Luenberger gözlemcisi gibi model tabanlı tahmin ediciler ve yapay sinir ağı ve makine öğrenimi yöntemleri gibi veri odaklı tabanlı modelleme teknikleri kullanılarak gerçekleştirilmektedir. Bu çalışma, bir batarya şarj durumu tahmin yöntemi geliştirmeyi amaçlamış ve genişletilmiş makine öğrenmesi (ELM) kullanarak çoklu batarya geri SOC tahmini için yeni bir mimari önermiştir. ELM yaklaşımı, küresel araç sürüş profilleri, Yeni Avrupa Sürüş Döngüsü ve Dünya Çapında Uyumlaştırılmış Hafif Araçlar Test Prosedürü kullanılarak ve akü çalışma koşulları dikkate alınarak uygulanmıştır. Önerilen SOC tahmin yönteminin performansı istatistiksel kriterler (RMSE, R2, MAPE) kullanılarak değerlendirilmiştir. Çalışma sonunda elde edilen sonuçlar, daha az karmaşık bir yapıya sahip veri güdümlü bir ELM yaklaşımının, farklı çalışma koşulları altında diğer gelişmiş tahmin yöntemlerine kıyasla daha iyi performans elde edebileceğini göstermektedir.

Anahtar Kelimeler: Genişletilmiş makine öğrenmesi, Şarj durumu, Tahin, Lityum-İyon, Batarya

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1. INTRODUCTION

The past twenty years have seen increasingly rapid advances in the field of rechargeable lithium-ion battery (LIB) energy storage system technologies of battery management systems (BMS) such as electric vehicles (EVs) and hybrid electric vehicles (HEVs). In the systems, the estimation of state-of-charge (SoC) which denotes the battery level is one of the greatest challenges because the parameter cannot be directly measured by a sensor. The SoC parameter is estimated using internal resistances and time constants of the battery dynamics and is monitored by the BMS to provide safe and reliable driving conditions (Baba et al., 2016). Besides safety, there are two critical operating conditions in a battery, over-charging and over-discharging. The over-charging state is above the specified upper limit of charging while over-discharging indicates that below the lower battery limit voltage. In this context, it is very important to precisely estimate SOC value to avoid mentioned states (Ahmed, El Sayed, Arasaratnam, Tjong, & Habibi, 2014; Baba & Adachi, 2014)

In practical applications, the SoC estimation process is carried out in different ways such as the coulomb counting method in which the estimation is calculated by integration of current, data-driven estimation method, model-based methods. In the first estimation method, the coulomb counting method is called as open-loop method and this method is sensitive to an initial value of SoC, will suffer from the cumulative integral error of current measurement (Ng, Moo, Chen, & Hsieh, 2009; Tong, Lacap, & Park, 2016). Model-based SoC estimation has been applied in many studies due to advancement in battery technologies (Jiang et al., 2021a). There are many different types of battery models in the literature each suitable for different structures and with a different level of complexity, from the electrochemical models to more advanced equivalent circuit models and electrochemical impedance models. Electrochemical battery models have been preferred for the modelling of battery chemical dynamics in the literature because these models express the physical dynamics of the li-on battery under different operating conditions (Ahmed et al., 2014, 2015). Besides, different observer structures have been implemented to these models such as adaptive square root extended Kalman filter (Plett, 2004), unscented Kalman filter (He, Williard, Chen, & Pecht, 2013; Zheng et al., 2018), adaptive Luenberger observer (Hu, Sun, & Zou, 2010), adaptive sliding mode observer (Belhani, M'Sirdi, & Naamane, 2013). However, the created observer and filter structures using physical models require precise and global mathematical modelling of the battery.

In contrary to physical modelling techniques, data-driven or machine learning-based modelling methods use the real-world input/output data of the system to model unknown dynamics. Since the models obtained using this method do not require a precise model and a formulation for dynamic and complex battery systems, machine learning algorithms such as artificial neural networks (Dang et al., 2016; Shen, Chan, Lo, & Chau, 2002), particle swarm optimization (Hossain Lipu, Hannan, Hussain, & Saad, 2017), support vector machines (Jiang et al., 2021b) have been applied to estimate the value of battery SOC. Different parameters (battery cell ageing, variable environmental conditions and other nonlinear states) have been easily incorporated into these created models (Tong et al., 2016). Although data-driven techniques are successful in accurately estimating the SOC value of batteries, they require cumbersome and time-consuming processes like online parameter adaption and computational burden on hardware.

More recently, single hidden layer feedforward neural network-based extreme learning machines (ELM) have been proposed to predict future actions of a physical system that included unknown dynamics by effectively analyzing collected big data on the system. This method has shown good performance in terms of learning speed and generalization compared to another conventional feedforward neural network (Huang, Chen, & Babri, 2000; Huang, Zhu, & Siew, 2006). For this purpose, the ELM has been used in different areas such as automatically driving based on camera vision (Zhu, Miao, Hu, & Qing, 2014), pattern classification (Liu & Wang, 2010), image deblurring (L. Wang, Huang, Luo, Wang, & Luo, 2011).

In this study, a key contribution is that this study the ELM estimator has been designed to create a Li-ion battery model to develop SOC estimation with 1D AVL Cruise M platform. In the proposed ELM predictive model, voltage, current, power and motor load of battery and vehicle speed have been considered as input parameters for SOC parameter prediction. Compared with the previous works, the main contributions of this paper are summarized as follows: (1) The created ELM estimator has been realized SOC value estimation of a battery without the need for a complex mathematical model like electrochemical and advanced equivalent circuit models under different environmental and driving cycle conditions. (2) Furthermore, fewer battery parameters according to neural networks and other data-driven based methods have been needed to estimate the battery SOC value in the training process of the ELM model. (3) The predictive performance of the ELM model has been evaluated under different both at variable conditions like both New European Driving Cycle (NEDC) and Worldwide harmonized Light vehicles Test Procedure (WLTP) driving cycles based on performance indices, including RMSE (Root mean squared error), R^2(Coefficient of determination), MSE (mean squared error), MAE (mean absolute error).

The paper is organized as follows: In Section II, the advanced equivalent circuit based mathematical analysis is conducted for the li-ion battery are proposed and presented in detail. In Section III, the extended learning machine model is explained. In Section IV, some results and discussions are expressed. Finally, some conclusions are provided in Section V.

2. METHODOLOGY

2.1. The Battery SOC Definition

The battery SOC is used to defined the remaining capacity of the lithium-ion battery and is mathematically expressed as the ratio of the remaining battery capacity to the full capacity that can be delivered as follows.

$$SOC(t) = SOC((t_0) - \frac{\int_{t_0}^{t} \mu I_{Batt}(t)\mu}{C_{max}} \tag{1}$$

In (1), C_max is the maximum charge capacity of battery, in Ah, I_batt depicts the battery current that is assumed discharging is positive and μ is the Coulombic efficiency.

2.2. The Modelling of Lithium-ion Battery Based on Equivalent Circuit Approach

In this subsection, the equivalent circuit model that is commonly used in the literature is proposed. The simple analytical models are preferred since increasing the complexity of the model increases the uncertainty in the estimates of the parameters. However, these models can not accurately characterize the battery under overall different operating conditions. In the literature, the Thevenin circuit model (Jiang et al., 2021b; Y. Wang, Liu, Pan, & Chen, 2017) and second-order circuit model (S. Wang, Fernandez, Shang, Li, & Yuan, 2018) are preferred to define battery dynamics.

In this study, the Thevenin equivalent circuit model has been used as shown in Fig. 1.

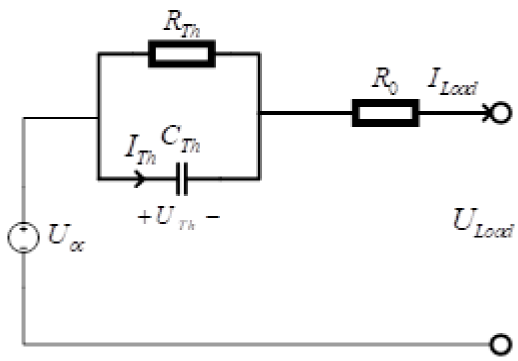

Figure 1:
Thevenin equivalent circuit model used for li-on battery

The dynamic behaviour of circuit can be mathematically defined as in Eq. (2) and Eq. (3).

$$U_{Th} = \frac{U_{Th}}{R_{Th} + C_{Th}} + \frac{I_{Load}}{C_{Th}} \tag{2}$$

$$U_L = U_{OC} - U_{Th} - I_L R_0 \tag{3}$$

Eq.(3), U_{TH}, U_{OC} and U_L are the voltage of across C_{Th} , open circuit and load, respectively. R_{Th}indicates polarization resistance and I_{Load} is load current.

2.3. Vehicle Modelling by Using AVL Cruise M

The estimation of SOC has been carried out using data obtained from a vehicle battery management system modelled by AVL Cruise M. The AVL Cruise M software offers both a graphical user interface, as well as command-line accessibility to create real-time capable subsystem models of engine, driveline, 1D fluid flow, aftertreatment, electrical and control system domains (Farag, Fleckenstein, & Habibi, 2014; Taborda, Varella, Farias, & Duarte, 2019; Zhang & Li, 2018).

During this study, the designed layout of AVL program is shown in Fig. 2. The specification of electrical motor, battery and vehicle are tabulated in Table 1.

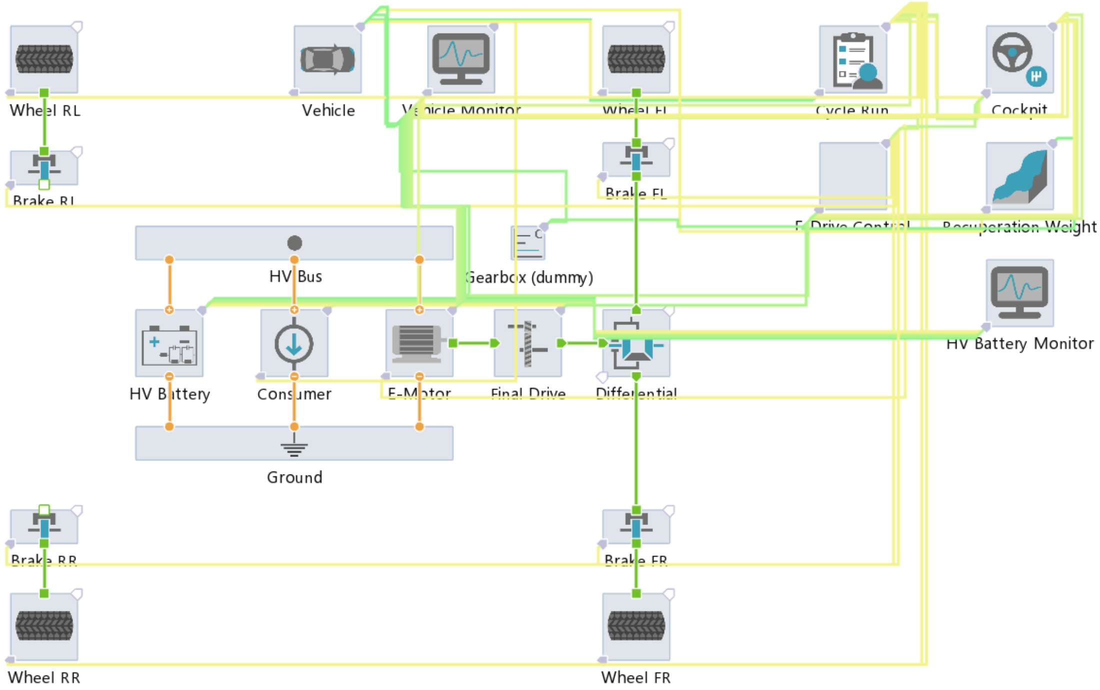

Figure 2:
The electrical vehicle AVL Cruise M model layout

Table 1. The specification of electrical motor, battery and vehicle used in this study

Type of electric machine	Asynchronous machine
Moment of intertia	0.08 kg.m^2
Battery minimum voltage	2.5 V
Battery maximum charge	20 Ah
Vehicle curb weight	1700 kg
Vehicle gross wight	1980 kg

2.4. Extreme Learning Machine (ELM) Model Formulation

The ELM algorithms suggested in this paper have been derived from the references (Huang, Zhou, Ding, & Zhang, 2012; Huang et al., 2006). The ELM algorithm is capable of learning for the single hidden-layer feedforward neural networks compared with traditional artificial neural networks and other machine learning algorithms. The output weights of ELM network structure are analytically defined according to the pseudo-inverse of the hidden-layer output matrix which is set randomly. To describe the ELM method mathematically, an unknown nonlinear dynamical system denoted as input ( ) in the following form is considered. Then, the output of the system is approximated using the ELM model as follows as expressed in (4)

$$F(x) = \sum_{j=1}^{HN} \theta_j h(a_j, b_j, x) \ldots \ldots . . x, a_j \in, \Re^n, \ldots . . b_j \in \Re \quad (4)$$

HN: Number of hidden layer

Where, a_i and b_i denote determined randomly coefficients of the hidden layer, θ_j is weight vector that connects to j hidden node from output node. $h(a_j, b_j, x)$ activation function of the network. The sigmoid, sine, triangular basis functions can be used as activation functions. To train the ELM network, training data and target data are considered as a set of training. So, output equation is obtained with hidden node output matrix as follows.

$$H\theta = Y \tag{5}$$

$$H = \begin{pmatrix} h(a_1, b_1, x_1) & \cdots & h(a_n, b_n, x_1) \\ \vdots & \ddots & \vdots \\ h(a_1, b_1, x_n) & \cdots & h(a_n, b_n, x_n) \end{pmatrix} \tag{6}$$

The used activation functions are Sigmoid.

The ELM algorithm is given as in the following form.

1. a_j, b_j, θ_j parameters are determined randomly by using continuous probability distribution function.
2. The general solution of equation given by (6) is treated as optimization problem by minimizing the following error in the last squares sense.

$$\min_{\theta}\left\{\frac{1}{2}\left\|[e_1^T, \dots, e_n^T]\right\|_F^2\right\} = \min_{\theta}\left\{\frac{1}{2}\left\|[(y_1^T - x_1^T), \dots, (y_n^T - x_n^T)]\right\|_F^2\right\} \tag{7}$$

Subject to

$$Y = H\theta + E \tag{8}$$

3. The solution of (7) is archived by

$$\theta = H^{\dagger}Y \tag{9}$$

Where $H^{\dagger}$ denotes the Moore-Penrose generalized inverse of matrix H. So, (9) can be written as follows and it is solved by singular value decomposition.

$$\theta = H^{\dagger}Y = (H^T H)^{-1} H^T Y \tag{10}$$

2.5. ELM model evaluation parameters

For evaluation, the root mean squared errors (RMSE), e coefficient of determinant (R) and mean absolute percentage error (MAPE) are proposed as the performance indexes, mathematically expressed by (11),(12),(13), respectively.

$$RMSE(y_{soc}, \hat{y}_{soc}) = \sqrt{\frac{\sum_{i=1}^{N}(y_{soc} - \hat{y}_{soc})^2}{N}} \tag{11}$$

$$R^2(y_{soc}, \hat{y}_{soc}) = 1 - \frac{\sum_{i=1}^{N}(y_{soc} - \hat{y}_{soc})^2}{\sum_{i=1}^{N}(y_{soc} - y_{soc_{mean}})^2} \tag{12}$$

$$MAPE(y_{soc}, \hat{y}_{soc}) = \frac{100}{N}\sum_{i=1}^{N}\frac{|y_{soc} - \hat{y}_{soc}|}{y_{soc}} \tag{13}$$

Where $\hat{y}_{soc}$ indicates battery SOC valur estimation of measured y_{soc}. By definition, the smaller calculated performance index value given in (11),(12),(13), the better estimation performance is obtained.

3. RESULTS AND DISCUSSION

To confirm the effectiveness of the proposed ELM method, the relationship between selected inputs and SOC parameters of li-ion battery has been realized. The vehicle battery group voltage, current, power, electrical motor load and vehicle speed has been used as the input parameters while SOC has been used as target data for ELM. The ELM structure used for modelling and estimation has been presented in Fig. 3.

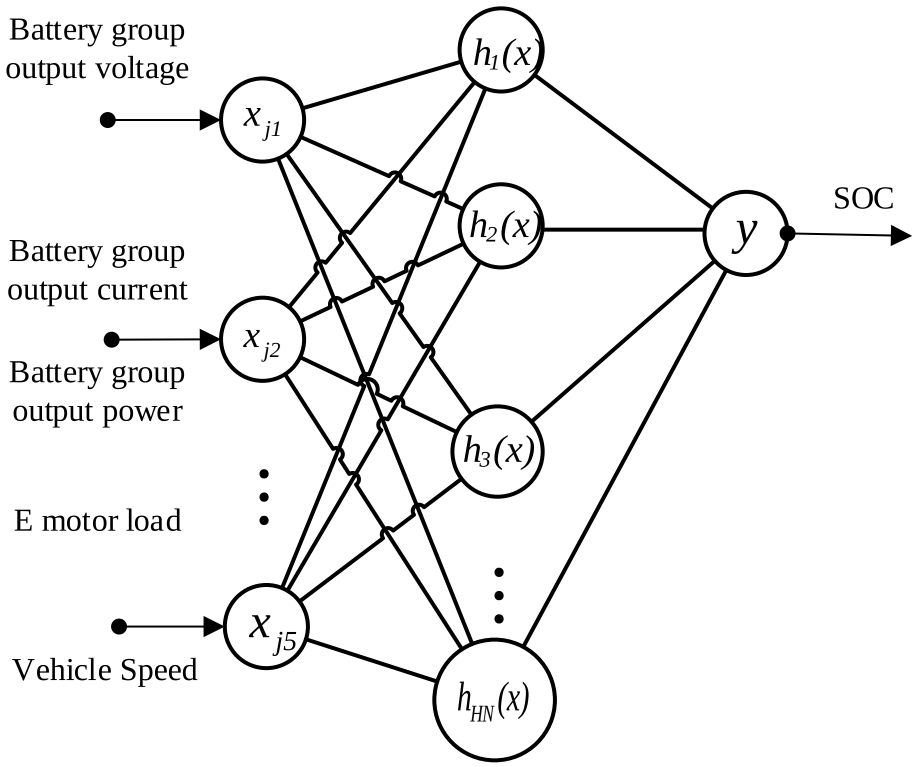

Figure 3:
Extreme learning machine SOC model for li-ion battery

In the first stage of the modelling process, the variable operating conditions have been carried out to validate the application and efficiency of the ELM on SOC estimation. For this purpose, the battery discharging voltage tills the terminal voltage declines to 2.5V, under New European

Driving Cycle (NEDC) and Worldwide harmonized Light vehicles Test Procedure (WLTP) driving cycles shown in Fig. 4, respectively.

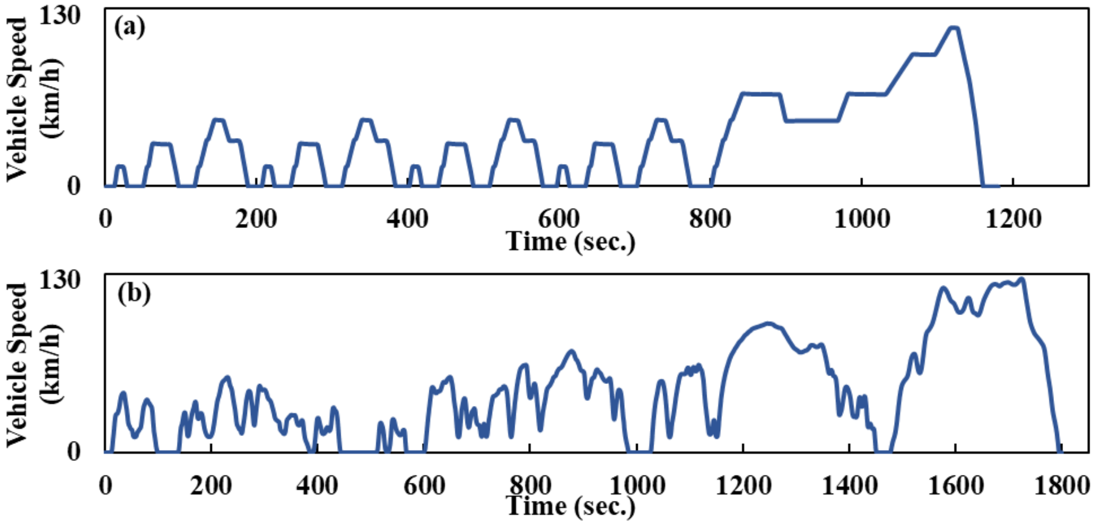

Figure 4:
Driving cycles (a) New European Driving Cycle (NEDC); (b) Worldwide harmonized Light vehicles Test Procedure (WLTC)

The NEDC and WLTC are typical vehicle driving cycles that are widely used to test the emission levels such as NOx, HC (Hydrocarbon) of automotive engines fuel consumption rate in vehicles. In this study, SOC values, its prediction errors for each driving cycles are compared, respectively. For the modelling process of battery, motor current, voltage, power and load presented in Fig. 5 and Fig. 6 are considered as input parameters for NEDC and WLTC driving cycles, respectively.

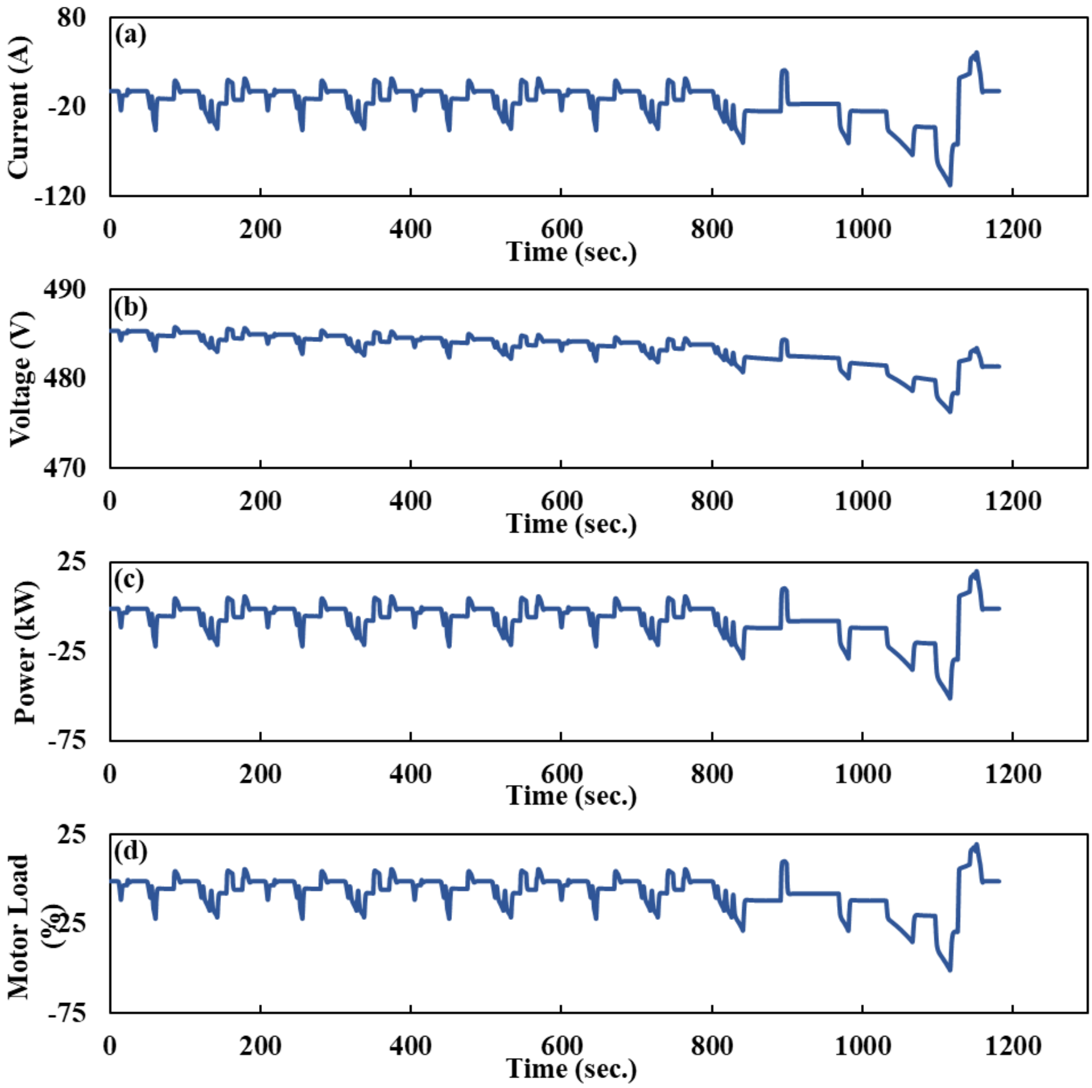

Figure 5:
Input parameters of ELM model under NEDC operating conditions (a) Battery voltage (b) Battery current (c) Power and (d) Electric motor load

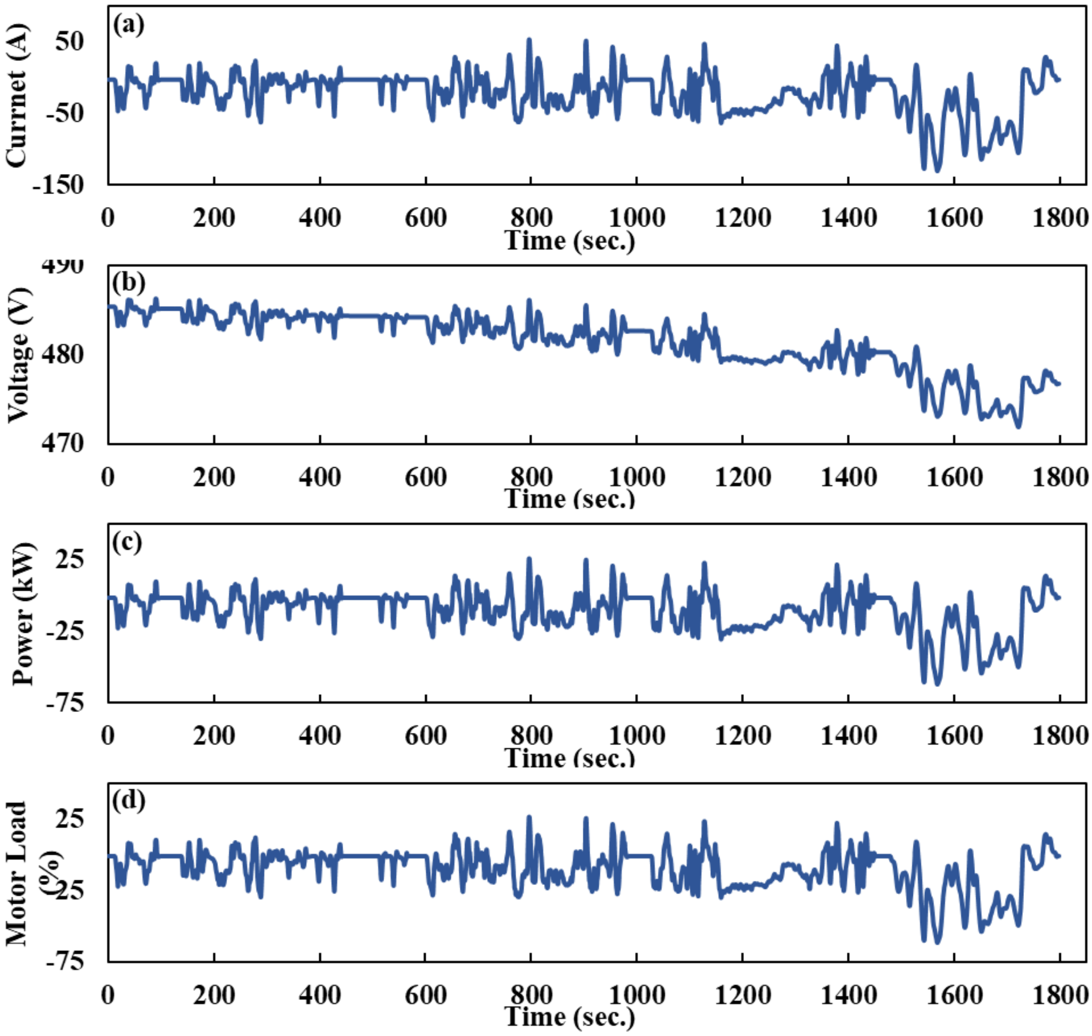

Figure 6:
Input parameters of ELM model under WLTC operating conditions (a) Battery voltage (b) Battery current (c) Power and (d) Electric motor load

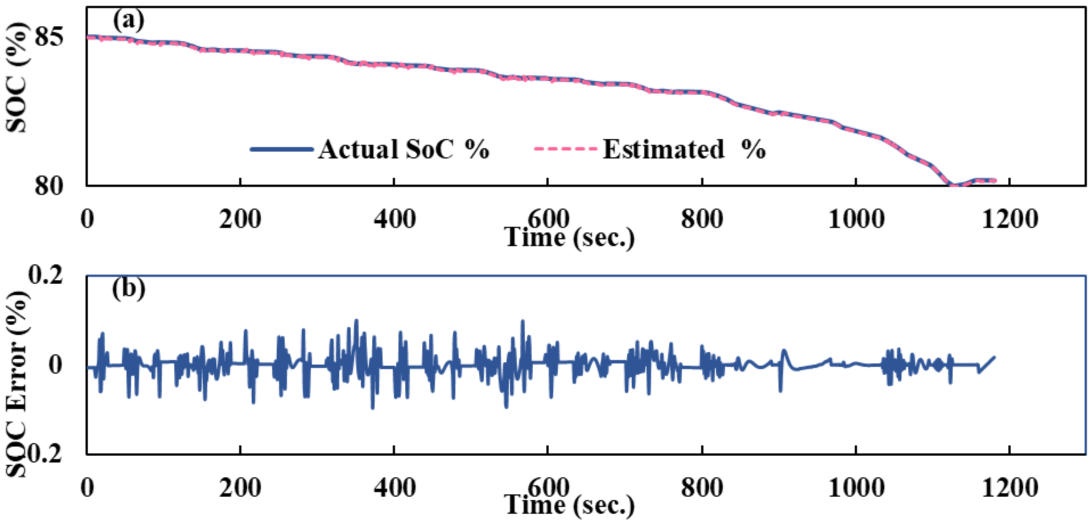

Figure 7:
Comparison of the estimation results under NEDC conditions; (a) SOC estimation, (b) SOC estimation error

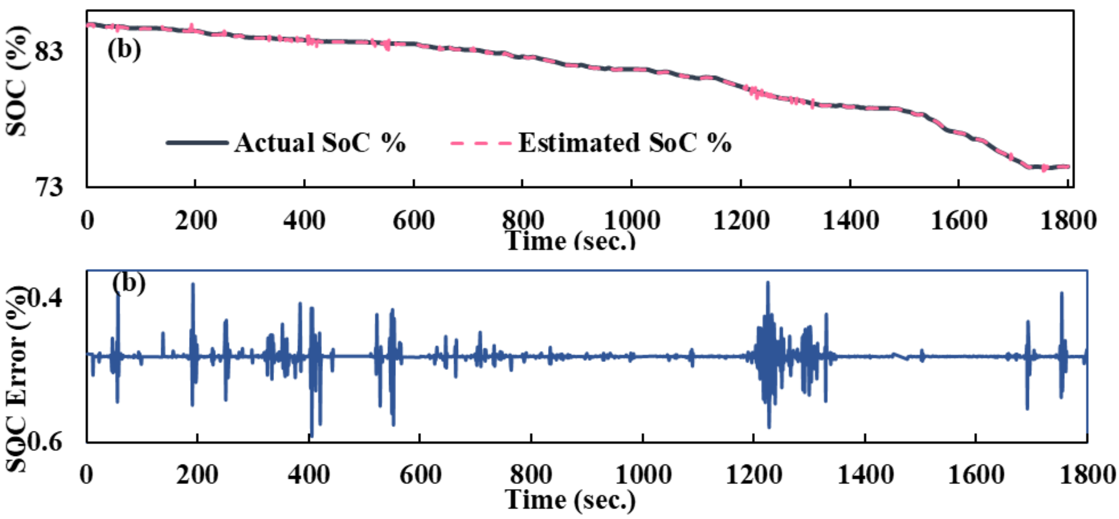

Figure 8:
Comparison of the estimation results under WLTC conditions; (a) SOC estimation, (b) SOC estimation error

As can be seen in these figures, the proposed ELM method presents good tacking performance under different vehicle transient conditions. From the Fig 7(a) and 8(a) SOC estimation results, it can be observed that error is within the range of 0.1% and -0.1% values for NEDC conditions while it variables between 0.4% and -0.4% for WLTC conditions. The SOC value in WLTC conditions has approximately decreased to 73% since the WLTC driving cycle takes longer than NEDC cycle. In addition, to analyze the SOC estimation tracking performance statistically, the detailed statistical analysis of different errors has been presented in Table 2i including the root of mean square error (RMSE), coefficient of regression (R2) and mean absolute percentage error. The fitness of the model has been calculated by assessing the coefficient of regression obtained from the analysis of variance (ANOVA).

Table 2. The specification of electrical motor, battery and vehicle used in this study

Vehicle Driving Cycles	RMSE	R^2	MAPE
NEDC	0.000117	0.999551	0.015373
WLTC	0.002072	0.999755	0.026207

It can be seen from figures and Table 2 including evaluation parameters that the results for the SOC estimation using ELM model is in excellent agreement with actual values obtained from li-ion battery under different vehicle driving profiles.

4. CONCLUSIONS

This paper has proposed a novel estimation of lithium-ion battery SOC with an extended learning machine-based modelling technique. The main conclusions of this study can be presented in the following form.

- The battery SOC estimation model has been developed with different methods in the literature. However, the proposed ELM algorithm has advantages such as light calculation, short time-consuming according to complex calculation methods. The ELM model has been created
- In this study, AVL Cruise M and MATLAB software as a combined program has been used to model the lithium-ion battery. The effectiveness of the developed model using this software and ELM based estimation strategy have been evaluated model accuracy and statistical methods in state-of-charge estimation.
- The proposed ELM model prediction performance has been evaluated through different global driving cycles; NEDC and WLTC. The results obtained show that better performance has been obtained by the developed ELM model.
- Unlike previous studies, the proposed ELM method has been utilized for SOC estimation of multiple li-ion battery package and good prediction performance has been obtained according to other estimation methods.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTION

Yusuf Alptekin TÜRKKAN: Configuration of paper, literature review, theoretical analysis.
Ali Rıza KALELİ: Determining and implementing the modeling process, writing, editing.

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