

Article

C-Rate- and Temperature-Dependent State-of-Charge Estimation Method for Li-Ion Batteries in Electric Vehicles

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Abstract: Li-ion batteries determine the lifespan of an electric vehicle. High power and energy density and extensive service time are crucial parameters in EV batteries. In terms of safe and effective usage, a precise cell model and SoC estimation algorithm are indispensable. To provide an accurate SoC estimation, a current- and temperature-dependent SoC estimation algorithm is proposed in this paper. The proposed SoC estimation algorithm and equivalent circuit model (ECM) of the cells include current and temperature effects to reflect real battery behavior and provide an accurate SoC estimation. For including current and temperature effects in the cell model, lookup tables have been used for each parameter of the model. Based on the proposed ECM, the unscented Kalman filter (UKF) approach is utilized for estimating SoC since this approach is satisfactory for nonlinear systems such as lithium-ion batteries. The experimental results reveal that the proposed approach provides superior accuracy when compared to conventional methods and it is promising in terms of meeting electric vehicle requirements.

Keywords: electric vehicle; equivalent circuit model; lithium-ion battery; state of charge; unscented Kalman filter



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1. Introduction

Due to their impact on air pollution and the greenhouse effect, global vehicle technology leaders have been transitioning from conventional vehicles to electric vehicles (EVs). Battery technology has had a notable impact in terms of the EV industry. With the high power and energy density, compact size, lower self-discharge, and extensive service life of Li-ion batteries, the electrification process has been further accelerated. However, lithium-ion batteries suffer from environmental effects and inappropriate usage. To maintain a reliable and efficient service life, a battery management system is crucial [1–3].

A battery management system, while providing safe operation during the life-cycle of the battery, also keeps the user and other subsystems informed of the vehicle's state of charge (SoC) [4]. The SoC indicates the charge left in the battery. It has a critical purpose of identifying vehicle operations and providing safe driving. For a consistent operation, the maximum SoC estimation error must be under 3% according to EV manufacturers and researchers [5]. To achieve this ratio, various SoC estimation techniques have been studied and published in the literature like open-circuit voltage (OCV)-based methods, Coulomb counting methods (CCMs), data-driven-based methods (DDBMs), and model-based methods (MBMs) [4,6].

The CCM is a common implementation in industry and among researchers due to its ease of implementation and simplicity [7,8]. However, CCMs suffer from initial SoC estimation errors, accumulating sensor measurement errors, and a Coulombic efficiency which is difficult to determine under different conditions [8,9].

OCV methods are also simple to implement, but they require a long rest time after charge/discharge periods, which makes it difficult to use this method for online SoC estimation [10]. The flat zone in the SoC/OCV curve is another bottleneck for this method [11]. Particularly, the batteries that have the LiFePO_4 chemistry suffer from the flat zone when estimating the SoC with the OCV method [11,12].

Data-driven-based methods have made great improvements with regard to SoC estimation accuracy and have solved the limitations that the OCV and CCM methods suffer from [13,14]. However, DDBMs require a lot of training datasets to attain a precise SoC estimation due to the sensor measurement noise that comes from training datasets [13,15]. Another difficulty of the DDBM is its powerful computer requirements because its complexity and computational effort make it difficult to implement in industrial applications [16,17].

MBMs are widely used among SoC estimation approaches to handle the bottlenecks of the common and data-driven-based methods [3,6,11,13,15,16,18–20]. MBMs consist of a battery equivalent circuit model (ECM) and one or more filtering approaches to estimate the SoC more accurately [21]. The ECM includes battery model parameters such as R , C , and OCV [22,23]. The model-based SoC estimation precision relies on the prediction accuracy of the battery model parameters [24]. Offline and online parameter prediction methods have been proposed by various researchers [25–27]. The operating temperature, C-rate, and aging rate are the most important factors in ECM parameter prediction [24]. Online parameter estimation methods, while achieving certain requirements in identifying battery parameters under different conditions, also increase complexity [28]. The number of RC parameters in the model also affects the accuracy. The first-order (one RC) ECM is the uncomplicated ECM model concerning battery modeling. While it requires less data when compared to higher-order ECM models, it cannot simulate real battery behavior properly. Therefore, higher-order ECMs are preferred in the literature to increase model accuracy [29].

Due to their suitability, robustness, and estimation accuracy rate, the Kalman filter and its extensions are the most popular state estimation filters for estimating SoC [18,30,31]. The pure Kalman Filter algorithm, while solving many estimation problems in different fields, cannot achieve sufficient estimation accuracy in terms of SoC estimation, because of the nonlinear behavior of the Li-ion batteries [13]. Among nonlinear Kalman filter techniques, the extended Kalman filter (EKF) is the most preferred battery SoC estimation algorithm [32,33]. The EKF works based on the linearization of nonlinear equations which use the first-order Taylor series expansion and partial derivatives [34,35]. Jacobian matrix computation is essential throughout state prediction, which highly affects the SoC estimation accuracy while using the EKF [36]. Using first-order Taylor series is a restriction of the extended Kalman filter approach since only the first-order accuracy is achievable when the first-order Taylor series is used [19]. Another dependency of the EKF algorithm for SoC accuracy is previous knowledge accuracy. Incorrect previous knowledge may increase the estimation error of the next cycle. To decrease the accuracy error portion that is affected by incorrect previous knowledge, aging- and temperature-dependent SoC estimation algorithms have been proposed by authors [5,19,34,37].

The Sigma-point Kalman filter (SPKF) is a favorable approach that, while achieving second-order estimation accuracy, can handle the EKF method's limitations [38]. The unscented Kalman filter (UKF), which is an augmentation of the SPKF, is commonly used as the SoC estimation algorithm [39]. The unscented Kalman filter provides better accuracy when compared to the EKF, because it uses a higher-order Taylor series expansion and avoids the Jacobian matrix calculation in the phase of linearization [32,40,41].

Hybrid SoC estimation algorithms have also been popular recently in the literature in increasing estimation accuracy and robustness [42,43]. Li et al. [44] proposed an EKF- and UKF-based SoC estimation algorithm to achieve a more robust and accurate estimation. In this study, while the EKF algorithm was used for online parameter estimation, the UKF algorithm was used for SoC estimation [44].

Pressure and humidity are two factors that notably affect cell behavior. Research shows that a humid environment can increase the self-discharge rate of batteries, which

cause energy loss. In this case, the SOC estimation algorithms might not be accurately estimated, because of the self-discharge [45]. In addition, a study investigating the impact of humidity on battery management system hardware found that humidity can affect electronic components, potentially leading to measurement errors that contribute to SOC estimation inaccuracies [46].

An uneven pressure on Li-ion cells notably varies their degradation rate and can lead to short circuits [47–49]. Conversely, another study indicates that a consistent pressure distribution within the cell enhances the cycle life of Li-ion batteries [50]. Pressure not only impacts capacity degradation but also influences the voltage response of Li-ion batteries [51]. Given that cell voltage is a critical data point used in SOC estimation algorithms, pressure changes may indirectly affect SOC estimation accuracy.

This paper proposes a C-rate- and temperature-dependent SoC estimation technique for EV applications. The ECM used in the proposed method covers a broad temperature range from $-10\text{ }^{\circ}\text{C}$ to $40\text{ }^{\circ}\text{C}$ and current rates of 1C, 1.5C, and 2C. The third-order ECM is utilized in this paper for better SoC estimation precision and robustness. To take account of the temperature and C-rate effects in the ECM, we use 3D lookup tables that are driven by the SoC, temperature, and C-rate. For managing the nonlinear characteristics of the Li-ion cell, the SoC estimation approach takes advantage of the UKF [52]. The contribution of the proposed approach considers various current rates and covers a wide temperature range to increase SoC estimation accuracy. The results illustrate that the proposed UKF-based SoC estimation approach achieves superior accuracy in the entire C-rate and temperature range when compared to conventional methods. The experimental assessment result promises that the proposed approach fully satisfies the EV implementation requirements in the accuracy base.

2. C-Rate- and Temperature-Dependent ECM

Figure 1 presents the generalized ECM of the cell. U_{oc} and V_t represent the open-circuit and terminal voltage of the cell, respectively. I denotes the input current. R_0 denotes the internal resistance, while R_i and C_i ($i = 1, 2, \dots, n$) represent the resistor and capacitor of the RC networks, respectively.

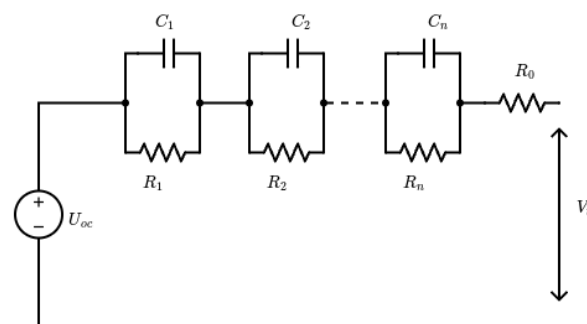


Figure 1. Generalized equivalent circuit model.

The voltage response of the ECM according to RC pair numbers is discussed in the literature [53]. The results prove that higher numbers of RC pairs in the ECM provide higher voltage prediction accuracies. However, it also increases the complexity. It is also known that higher-order ECMs increase the robustness of the algorithm [54]. Therefore, in the proposed approach, a 3RC ECM is used which provides better accuracy and robustness.

ECM parameters are not constant, due to the nonlinear behavior of the lithium-ion cells. The C-rate, SoC, temperature, and SoH affect the ECM parameters. For a more accurate battery model, voltage prediction, and SoC estimation, the ECM should be created by consideration of these affected factors. Temperature and C-rate have a remarkable effect on the ECM RC parameters. The figures provided in Appendix A demonstrate how ECM parameters change under different temperature and C-rate conditions. These figures demonstrate the notable impact of temperature and C-rate variations on ECM parameters. If the C-rate or

temperature is not considered, the SoC estimation algorithm accuracy might be affected negatively. Since including these factors in the model increases complexity and computation time, according to the intended use, the complexity and accuracy should be in balance. With all these considerations, a C-rate- and temperature-dependent third-order ECM is proposed. Figure 2 illustrates the general representation of the proposed ECM for a cell.

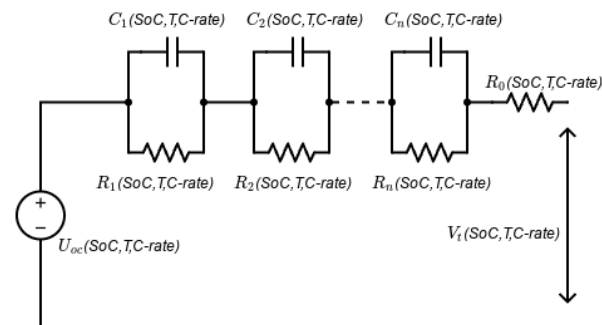


Figure 2. C-rate- and temperature-dependent ECM.

The current- and temperature-dependent SoC estimation method works based on the third-order ECM and its components are a function of C-rate, temperature, and SoC. To predict the parameters of the proposed ECM, a discharge pulse test is implemented under a wide temperature range from $-10\text{ }^{\circ}\text{C}$ to $40\text{ }^{\circ}\text{C}$ with $10\text{ }^{\circ}\text{C}$ intervals and for different C-rates of 1C, 1.5C, and 2C. The average cell capacity is 2.2 Ah and the test is repeated for 2.2 A, 3.3 A, and 4.4 A for each temperature condition. Thus, the voltage data of the discharge pulse test were collected for all test conditions. Figure 3 is given as an example of a discharge pulse test for $30\text{ }^{\circ}\text{C}$ and 2.2 A test conditions.

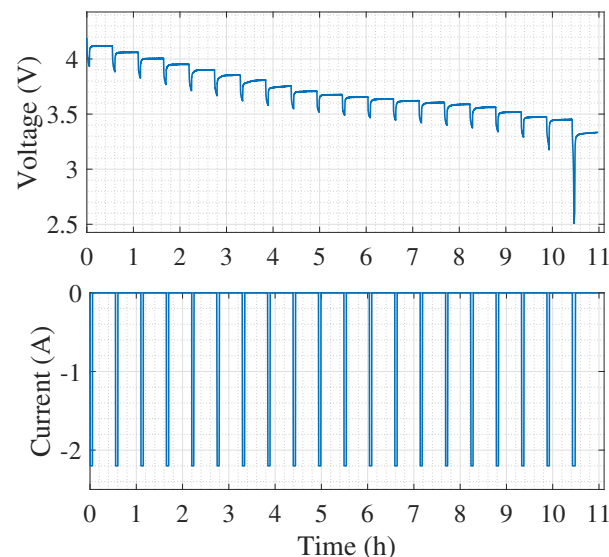


Figure 3. Discharge pulse test for $30\text{ }^{\circ}\text{C}$ and 1C current rate.

To simulate the Li-ion battery's behavior by the ECM model, the voltage curve of the discharge pulse test must be taken as a reference, because the voltage data of the experimental test provide the model parameter information, as seen in Figure 4. The reasons for the voltage drop and transient response are the R_0 and RC pairs, respectively. Thus, after obtaining the experimental results of the discharge pulse test, the R_0 and the RC parameters of the ECM can be calculated by voltage drops and the transient response, respectively. The ECM parameters of the proposed SoC estimation algorithm are predicted by the layered method [53].

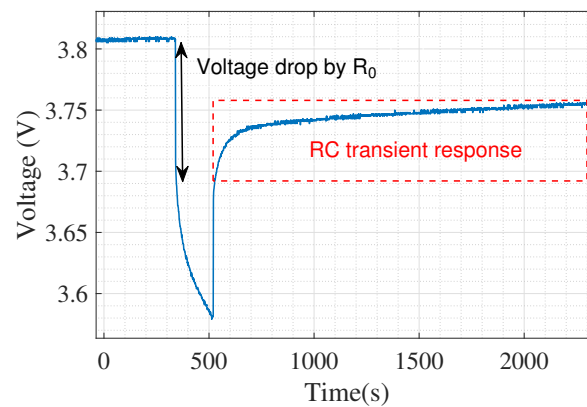


Figure 4. Voltage drop and transient response of the cell voltage.

3. Proposed SoC Estimation Method

Because of the nonlinear characteristics of the lithium-ion batteries, the linear Kalman filter approach does not have sufficient accuracy performance for estimating the SoC of the Li-ion batteries. The extended Kalman Filter (EKF) algorithm is widely used as an SoC estimation approach since it has remarkable results in the Li-ion battery's SoC estimation. However, the EKF algorithm works according to the first-order Taylor series during estimation and has limited accuracy in the solutions. As an improvement, a UKF approach is proposed which works based on the third-order Taylor series. The UKF utilizes the Unscented Transform which has a significant impact on the linearization process to achieve a more accurate state estimation when compared to the EKF [55]. The flow chart presented in Figure 5 illustrates the SoC estimation process by operating the UKF.

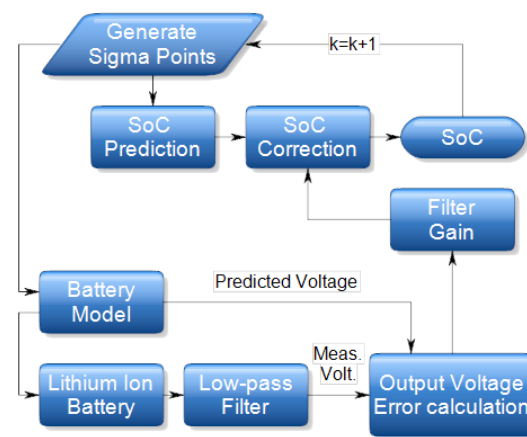


Figure 5. SoC estimation process with UKF.

To define the output statistic, the state vector unscented transform is calculated through (1) [56–58].

$$\left\{ \begin{array}{ll} \hat{x}_{k-1}^{(i)} = \hat{x}_{k-1}^+ + \tilde{x}^{(i)} & i = 1, 2, \dots, 2n \\ \tilde{x}^{(i)} = \sqrt{(n + \lambda)P_x} & i = 1, 2, \dots, n \\ \tilde{x}^{(n+i)} = -\sqrt{(n + \lambda)P_x} & i = 1, 2, \dots, n \\ w_0^m = \lambda / (n + \lambda) \\ w_0^c = \lambda / (n + \lambda) + (1 - \alpha^2 + \beta) \\ w_i^m = w_i^c = 1 / (2(n + \lambda)) & i = 1, 2, \dots, 2n \end{array} \right. \quad (1)$$

where x represents a Gaussian random variable with n dimensions. Its covariance and mean value are P_x and $\bar{x}$, respectively. The scaling parameter is defined as $\lambda = \alpha^2(n + k) - n$. α denotes the spread points of the sigma points around $\bar{x}$. $\hat{\alpha}$ presents the distribution of x according to prior incorporated knowledge. $\hat{\alpha} = 2$ is considered optimal in respect of

the Gaussian distribution. $\sqrt{(n + \lambda)P_x}$ represents the i^{th} column of the matrix square root for $(n + \lambda)P_x$. After that, each sigma point is disseminated through the function of $f(X_i)$, $i = 0, 1, 2, \dots, 2n$ [56–58].

Then, the covariance and mean of the system estimate are calculated in (2).

$$\begin{cases} \bar{y} = \sum_{i=0}^{2n} w_i^m y_i \\ P_y = \sum_{i=0}^{2n} w_i^c (y_i - \bar{y})(y_i - \bar{y})^T \\ P_{xy} = \sum_{i=0}^{2n} w_i^c (y_i - \bar{y})(y_i - \bar{y})^T \end{cases} \quad (2)$$

Algorithm 1 presents a summary of the UKF algorithm with respect to SoC estimation [59].

Algorithm 1. Summary of the UKF algorithm for SoC estimation

Initialization:

$$k = 0, \bar{x}_0 = E(x_0), P_0 = E[(x_0 - \bar{x}_0)(x_0 - \bar{x}_0)^T]$$

Computation: time update prior estimation (from $(k - 1)^+$ to $(k)^-$) for $k = 1, 2, 3, \dots$, compute

Sampling of sigma:

$$\begin{cases} \hat{x}_{k-1}^{(i)} = \hat{x}_{k-1}^+ + \tilde{x}^{(i)} & i = 1, 2, \dots, 2n \\ \tilde{x}^{(i)} = \sqrt{(n + \lambda)P_x} & i = 1, 2, \dots, n \\ \hat{x}^{(n+i)} = -\sqrt{(n + \lambda)P_x} & i = 1, 2, \dots, n \end{cases}$$

Weight calculation:

$$\begin{cases} w_0^m = \lambda / (n + \lambda) \\ w_0^c = \lambda / (n + \lambda) + (1 - \alpha^2 + \beta) \\ w_i^m = w_i^c = 1 / 2(n + \lambda) \quad i = 1, 2, \dots, 2n \end{cases}$$

Update the state:

$$\begin{cases} \hat{x}_k^{(i)} = A\hat{x}_{k-1}^{(i)} + Bu_k + \omega_k \\ \hat{x}_k^- = \sum_{i=0}^{2n} w_i^m \hat{x}_k^{(i)} \end{cases}$$

Update the error covariance:

$$P_{x,k}^- = \sum_{j=0}^{2n} w_j^c [\hat{x}_k^{(j)} - \hat{x}_k^-] [\hat{x}_k^{(j)} - \hat{x}_k^-]^T$$

Update the output:

$$\hat{y}_k^{(i)} = C\hat{x}_{k-1}^{(i)} + Du_k + v_k, \hat{y}_k^- = \sum_{j=0}^{2n} w_j^m \hat{y}_k^{(j)}$$

Measurement update posteriori estimation (from $(k)^-$ to $(k)^+$).

$$\begin{cases} P_{y,k} = \sum_{j=0}^{2n} w_j^c [\hat{y}_k^{(j)} - \hat{y}_k^-] [\hat{y}_k^{(j)} - \hat{y}_k^-]^T \\ P_{xy,k} = \sum_{j=0}^{2n} w_j^c \sum_{j=0}^{2n} w_j^c [\hat{y}_k^{(j)} - \hat{y}_k^-] [\hat{x}_k^{(j)} - \hat{x}_k^-]^T \\ L = P_{xy,k}^* P_{y,k}^{-1} \end{cases}$$

State estimate measurement update:

$$\hat{x}_k^+ = \hat{x}_k^- + L(y_k - \hat{y}_k^-)$$

Error covariance measurement update:

$$P_{x,k} = P_{x,k}^- - LP_{y,k} \times L^T$$

The proposed current- and temperature-dependent SoC estimation method was established using MATLAB Simulink R2023a. While this tool provides an ease of application and simulation in validating the proposed algorithm, it also has the advantage of the embedded implementation during experimental validation. This study also took advantage of embedded coding by Simulink.

4. Experimental Assessment

Because of the wide usage of NMC-type batteries, the Panasonic UR18650AA NMC-type lithium-ion cell was used in this study. The cells are manufactured by Panasonic Industry Co., Ltd. and sourced from Shenzhen City, Guangdong Province, China. The detailed cell specifications are given in Table 1.

Table 1. Panasonic UR18650AA cell specifications.

Item	Specifications	Unit
Max Voltage	4.2	(V)
Nominal Voltage	3.6	(V)
Cut-off Voltage	2.5	(V)
Nominal capacity (min.)	2150	(mah)
Nominal capacity (typ.)	2250	(mah)
Discharge C-rate (max)	2C	NA
Diameter (max)	18.5	(mm)
Height (max)	65.1	(mm)
Chemical abbreviation	NMC	NA
Cathode	LiNiMnCoO ₂	NA
Anode	carbon	NA

To extract the cell data, the cell sample is discharged under various temperature conditions ($-10\text{ }^{\circ}\text{C}$, $0\text{ }^{\circ}\text{C}$, $10\text{ }^{\circ}\text{C}$, $20\text{ }^{\circ}\text{C}$, $30\text{ }^{\circ}\text{C}$, $40\text{ }^{\circ}\text{C}$) and current values (2.2 A (1C), 3.3 A (1.5C), 4.4 A (2C)). To adjust the environmental temperature, the Nuve-TK600 model climatic test cabinet was used. Nuve-TK600 was manufactured by NÜVE SANAYİ MALZEMELERİ İMALAT VE TİCARET A.Ş. and sourced from Bursa, Turkey. The test cabinet is capable of keeping the temperature at adjusted temperature values in the range from $-10\text{ }^{\circ}\text{C}$ to $60\text{ }^{\circ}\text{C}$. For the discharge cycle, the PRODIGIT 3314F model electronic load was used to keep the discharge current stable on a specific current value. PRODIGIT 3314F was manufactured by Prodigit Electronics Co., Ltd. and sourced from Istanbul, Turkey. The test system is given in Figure 6.

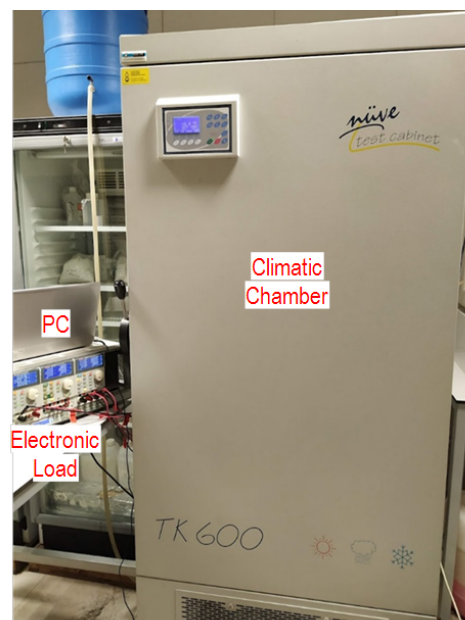


Figure 6. Cell test system for discharge pulse test.

During the discharge cycle, the NI USB-6001 data acquisition module was used to collect the measured current, voltage, and temperature values. NI USB-6001 is manufactured by NATIONAL INSTRUMENTS CORP. and sourced from Istanbul, Turkey. The STM32G431 evaluation board and a relay set were used with the proper connections and

software to automate the discharge cycle, as seen in Figure 7, for eliminating human factors on the measurements. STM32G431 evaluation board was manufactured by STMicroelectronics NV, and sourced from Istanbul, Turkey.

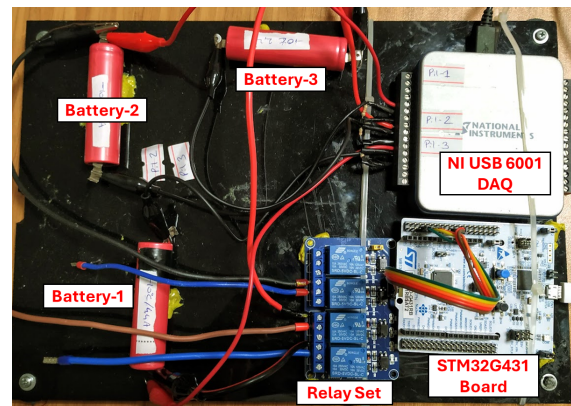


Figure 7. Data collection and automated cycler system.

Figure 2 illustrates the selected ECM for creating the cell model based on the 3RC pairs and its element dependent on C-rate, temperature, and SoC. In the proposed approach, the ECM parameters controlled by lookup tables are predicted by the layered method [53]. The data prove that C-rate and temperature have a significant influence on the model data, as shown in Appendix A. Since C-rate has a notable impact on the ECM parameters, and the SoC estimation algorithm relies on the ECM, it also affects the SoC estimation accuracy. To assess the proposed algorithm under different temperature and C-rate conditions, both the temperature and current must be varied during the experimental validation. To cover a wide range of temperatures during the algorithm validation test, the cell temperature varies between 5 °C and 40 °C, as given in Figure 8. The discharge process started at 4.2 V (fully charged) and finalized at 2.5 V (cut-off). The discharge current randomly changed in the range of rates from 1C to 2C, as shown in Figure 9, to cover the whole C-rate range that the predicted parameters are based on. There was a 30 min rest period after each discharge period and the test was stopped when the cell voltage hit 2.5 V. Current, temperature, and voltage were measured via sensing devices, and the measured data were transferred to an STM32F401RE evaluation board. The STM32F401RE evaluation board was manufactured by STMicroelectronics NV, and sourced from Istanbul, Turkey. The STM32F401RE evaluation board was used to operate the proposed algorithm depending on the collected data. During the experimental assessment, the SoC estimation result data were collected via serial communication and stored on the PC as illustrated in Figure 10.

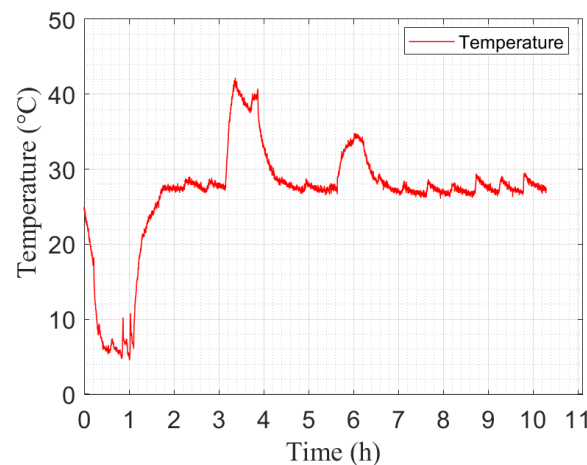


Figure 8. Cell temperature variation during algorithm validation test.

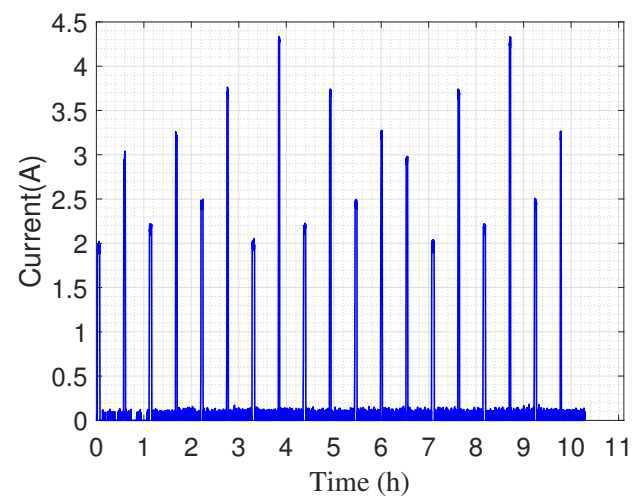


Figure 9. The random current applied to the algorithm validation test.

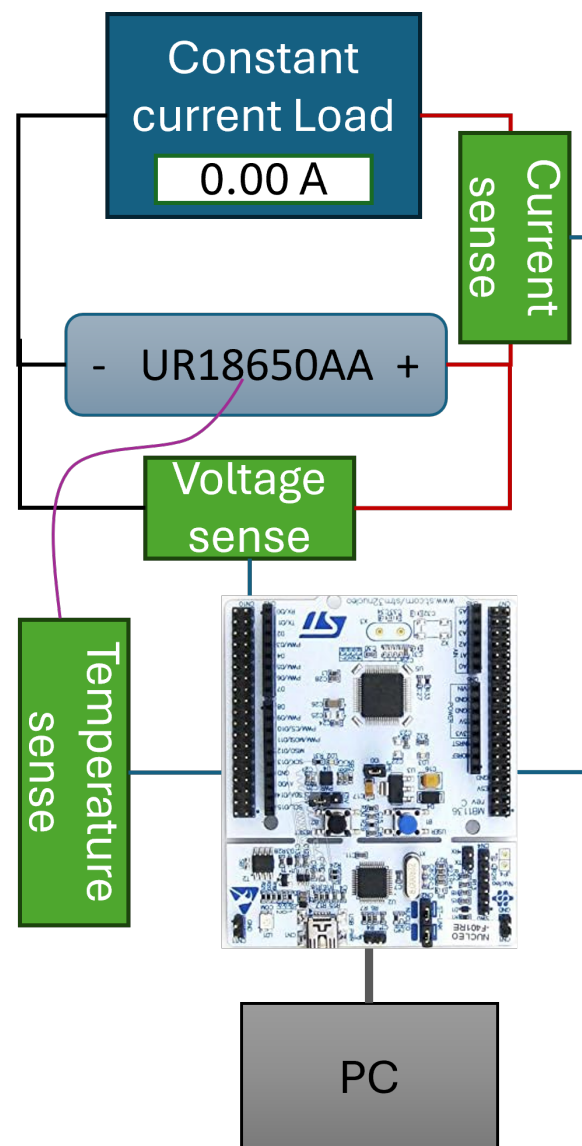


Figure 10. Experimental setup for algorithm assessment.

The experimental assessment reveals the efficacy of the proposed C-rate- and temperature-dependent SoC estimation method. In this experiment, the SoC-dependent SoC estimation method on its own, the temperature-dependent (conventional) SoC estimation method, and the proposed method are considered. Conventional Kalman filter-based SoC estimation algorithms do not consider the C-rate factor or only consider it within limited temperature and current ranges, and they typically use a second-order ECM [60,61]. The proposed UKF-based SoC estimation algorithm, while considering a wide range of temperatures and C-rates, also uses a third-order ECM, which provides robustness to the algorithm [54]. The SoC estimation results for the true initial SoC case are given in Figure 11.

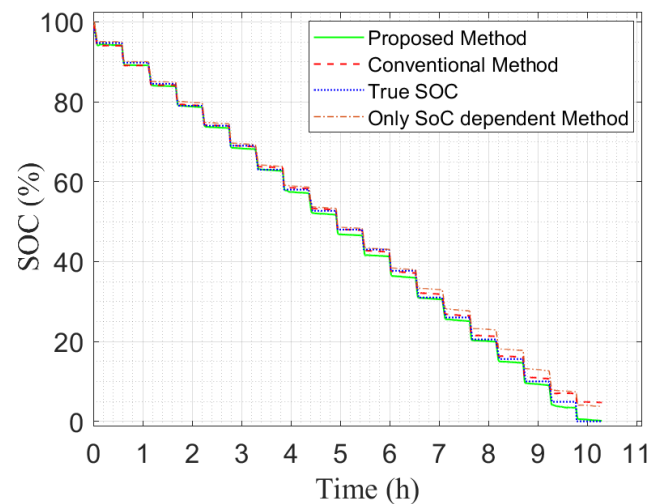


Figure 11. The result of the SoC estimation with true initial SoC for the considered methods.

Table 2 shows the maximum error and RMSE of the SoC-dependent method on its own, the conventional method, and the proposed method under various temperature conditions. All methods are run together on the evaluation board, and they are fed with the same inputs of the temperature, voltage, and current. Table 2 indicates that the proposed method has a lower maximum absolute error (MAE) and Root-Mean-Square Error (RMSE). The RMSE of the proposed method is below 1% and its MAE is below 3%. These results prove that the proposed method satisfies the SoC estimation requirements of electric vehicles powered by lithium-ion batteries.

Table 2. Error comparison for considered SoC estimation methods with true initial SoC.

Method	MAE (%)	RMSE (%)
Only SoC-dependent Method	5.61	0.91
Conventional Method	3.42	0.64
Proposed Method	2.2	0.48

Figure 12 shows the comparison of the proposed method, the conventional method, and the SoC-dependent method on its own with an inaccurate initial SoC. The proposed method has the best performance in terms of catching the true SoC faster according to other methods. The proposed method SoC result is almost the same as the true SoC after about 30 min, while the conventional method SoC curve follows the true SoC after 1 h. Besides that, the proposed method has a 10% maximum absolute error, while the conventional method and the SoC-dependent method on its own have 19% and 27% maximum absolute errors, respectively, with an inaccurate initial SoC.

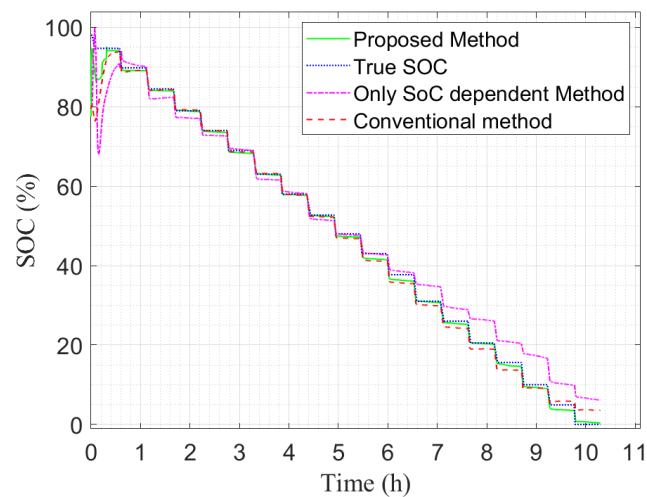


Figure 12. The result of the SoC estimation with incorrect initial SoC for the considered methods.

The considered methods have been compared to each other according to the UDDS and HUDDS drive cycles to estimate the SoC based on the electric vehicle real energy consumption behavior under different conditions. Figures 13 and 14 illustrate the estimation results for the UDDS and HUDDS drive cycles, respectively. The results demonstrate that the proposed approach has more accurate SoC estimation results according to the other methods.

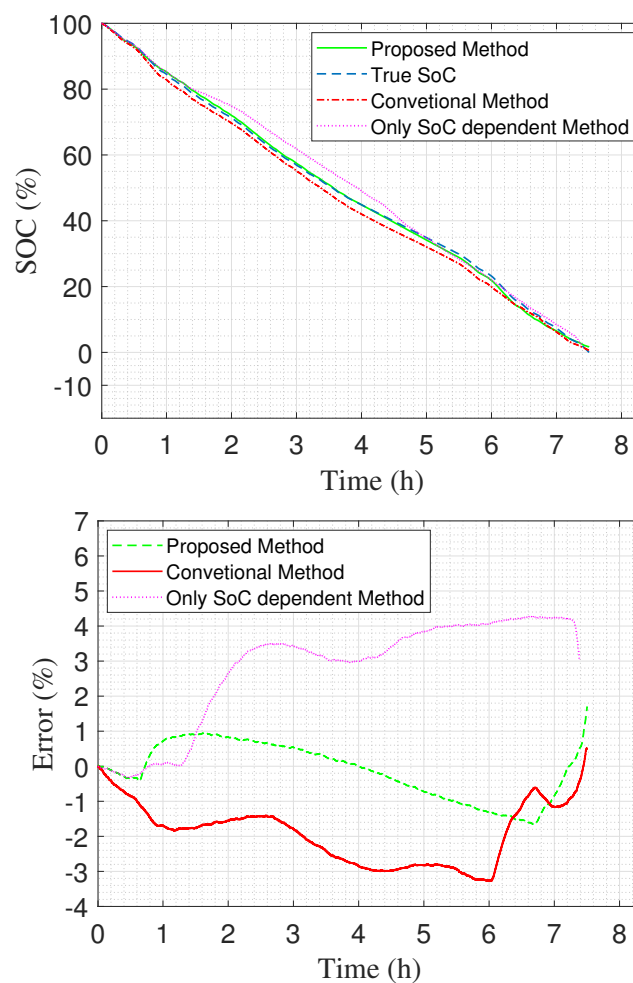


Figure 13. SoC estimation results comparison based on the UDDS drive cycle for the considered methods.

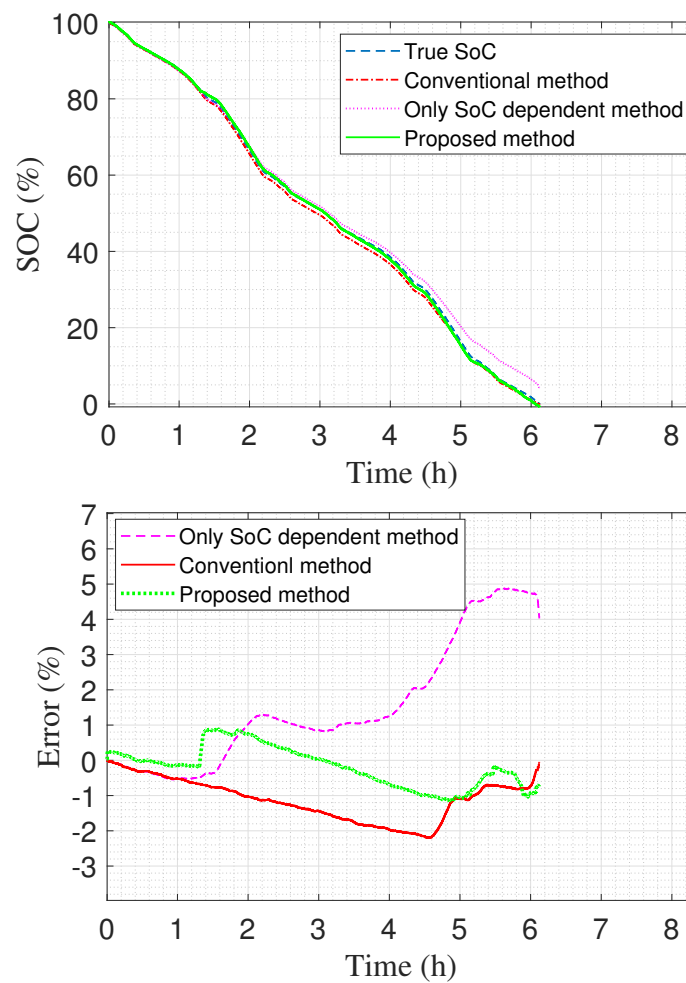


Figure 14. SoC estimation results comparison based on the HUDDS drive cycle for the considered methods.

According to the UDDS drive cycle test results, the SoC-dependent method on its own has a 4.2% MAE, the conventional method has a 3.22% MAE, and the proposed method has a 1.75% MAE. The HUDDS test results show that the SoC-dependent method has a 4.8% MAE, the conventional method has a 2.19% MAE, and the proposed method has a 1.14% MAE.

The figures given in Appendix A illustrate that the ECM parameters vary under different C-rate conditions. Since the proposed SoC estimation algorithm relies on these ECM parameters to predict battery behavior, considering the C-rate factor in addition to temperature significantly enhances the SoC estimation accuracy, as demonstrated in Figures 11–14.

The voltage measurement data play a key role in the UKF-based SoC estimation algorithm during both correction and prediction phases. However, due to possible measurement errors of the voltage sensors, the UKF-based SoC estimation algorithm accuracy may be compromised. The tested cell OCV-SoC curve, represented in Figure 15, demonstrates certain characteristics: significantly, there is a cursory slope between an SoC of 20% and 50%, indicating minimal voltage variance within this range. In contrast, regarding the end of discharge, the curve shows a steep slope, resulting in notably higher voltage differences compared to earlier SoC breakpoints.

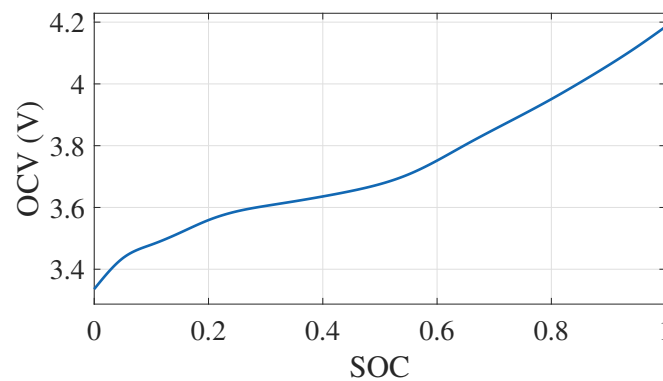


Figure 15. OCV-SoC curve.

During higher-voltage-difference phases, the UKF-based SoC estimation algorithm tends to preserve accurate SoC estimations. Conversely, when voltage differences between consecutive SoC breakpoints are small, SoC estimation errors can increase. In these scenarios, voltage measurement inaccuracies can significantly impact data quality and, as a result, worsen the SoC estimation accuracy. In Figures 12 and 14, regarding the end of the discharge cycle, the proposed SoC estimation method tends to correct the SoC estimation more effectively because of the higher voltage variance noticed during this phase.

5. Conclusions

In this paper, a current- and temperature-dependent SoC estimation method for Li-ion batteries in electric vehicles is proposed. The proposed SoC estimation method relies on the third-order current-, temperature-, and SoC-dependent ECM, which has a positive impact on the SoC estimation accuracy. This paper also proposed an unscented Kalman filter-based current- and temperature-dependent SoC estimation algorithm that is very useful for nonlinear systems such as Li-ion batteries. The experimental assessment reveals that the proposed method surpasses conventional methods in the entire current rate and temperature range in respect of the MAE and RMSE of the SoC estimation. The experimental results also show that the proposed method is capable of estimating the SoC more accurately in terms of catching the true SoC curve quicker and following the true SoC curve closer even in inaccurate initial SoC conditions when compared to the other considered methods. The results confirm that the proposed approach overcomes the electric vehicle requirements and is suitable for use in the EV industry.

As an improvement to the proposed method, the hysteresis effect of the Li-ion batteries must be considered. Cell degradation is another factor that may affect the SoC estimation when the cells age in time. Therefore, these factors will be the topic of the following study including the proposed method.

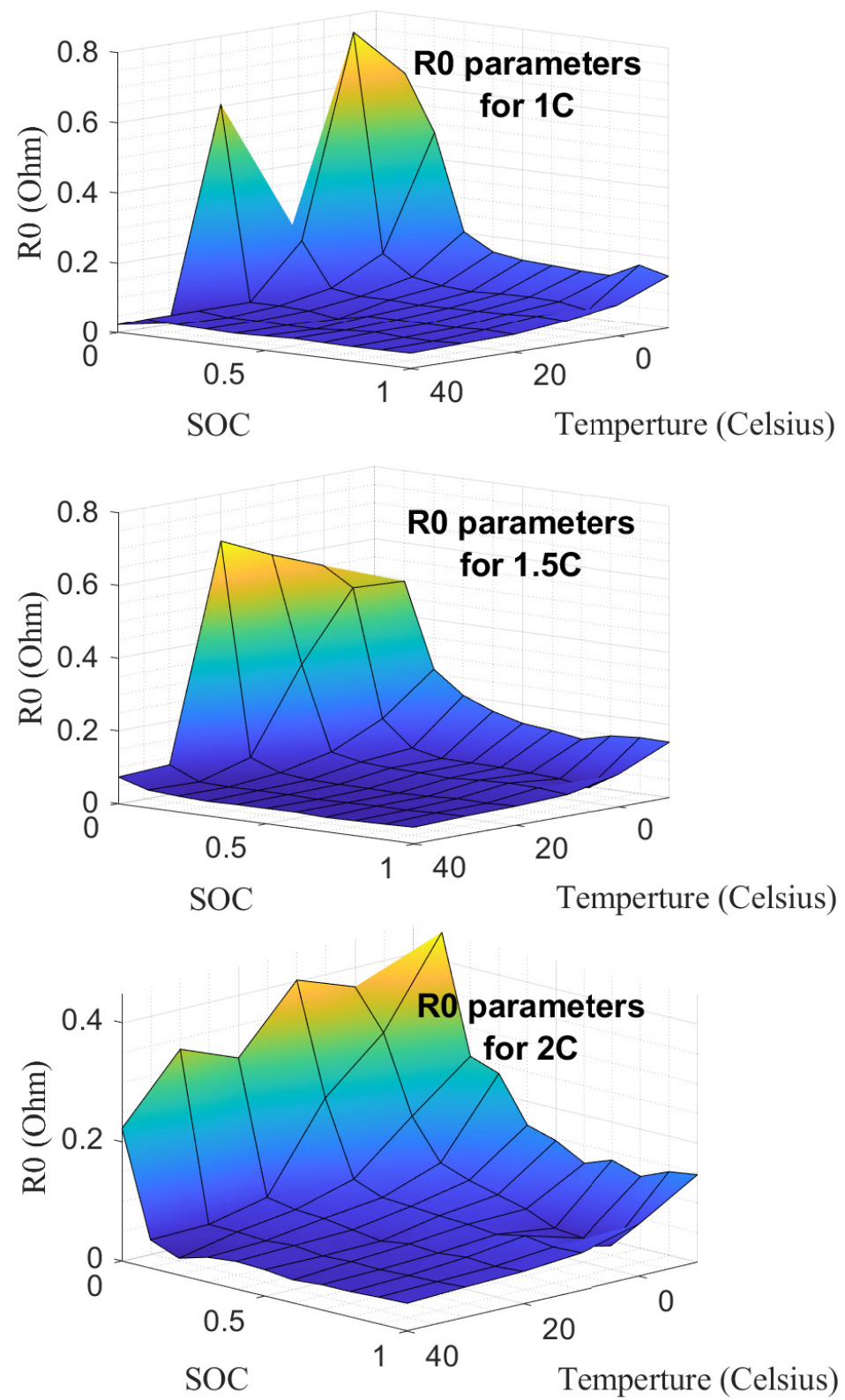
Author Contributions: Conceptualization, E.A.; Methodology, E.A.; Software, E.A.; Validation, E.A. and Y.Y.; Formal analysis, Y.Y.; Investigation, E.A.; Resources, E.A. and Y.Y.; Data curation, E.A.; Writing—original draft, E.A.; Writing—review & editing, E.A.; Visualization, E.A.; Supervision, Y.Y. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The datasets presented in this article are not readily available because the data are part of an ongoing study.

Conflicts of Interest: Author Eyyup Aslan was employed by the company Aurora Flight Sciences, a Boeing Company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A. C-Rate- and Temperature-Dependent ECM Parameters

**Figure A1.** R0 ECM parameters under different C-rate and temperature conditions.

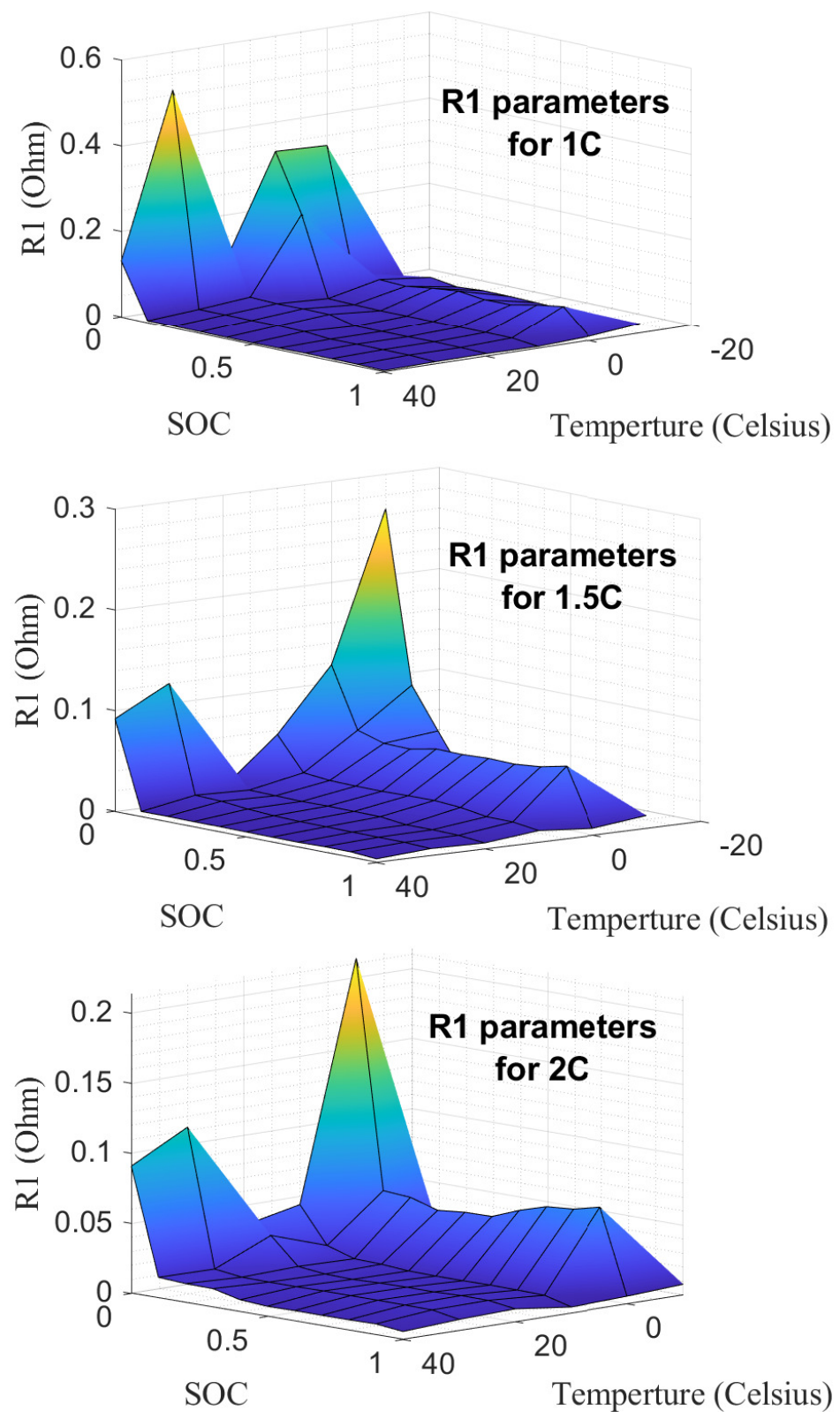


Figure A2. R1 ECM parameters under different C-rate and temperature conditions.

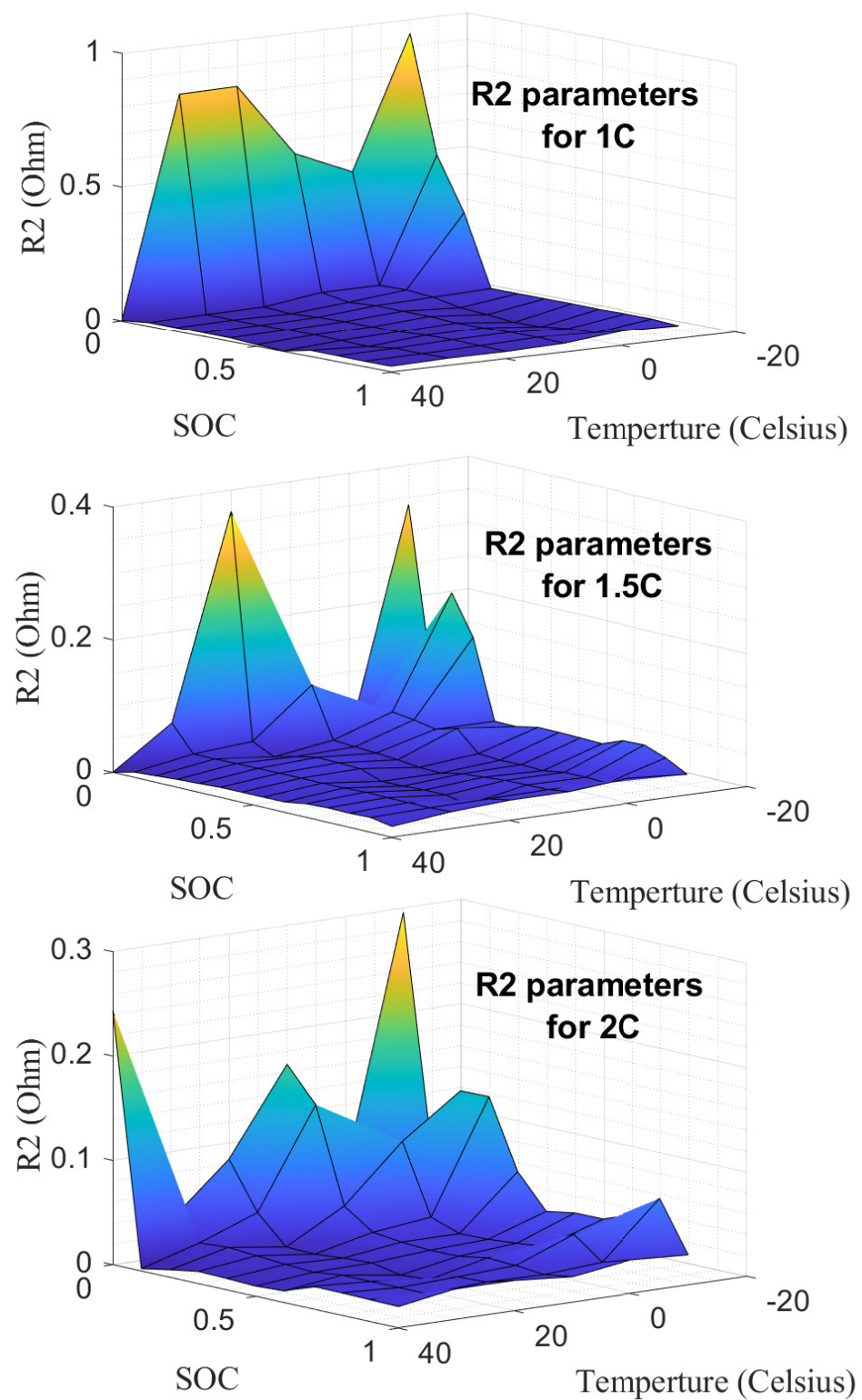


Figure A3. R2 ECM parameters under different C-rate and temperature conditions.

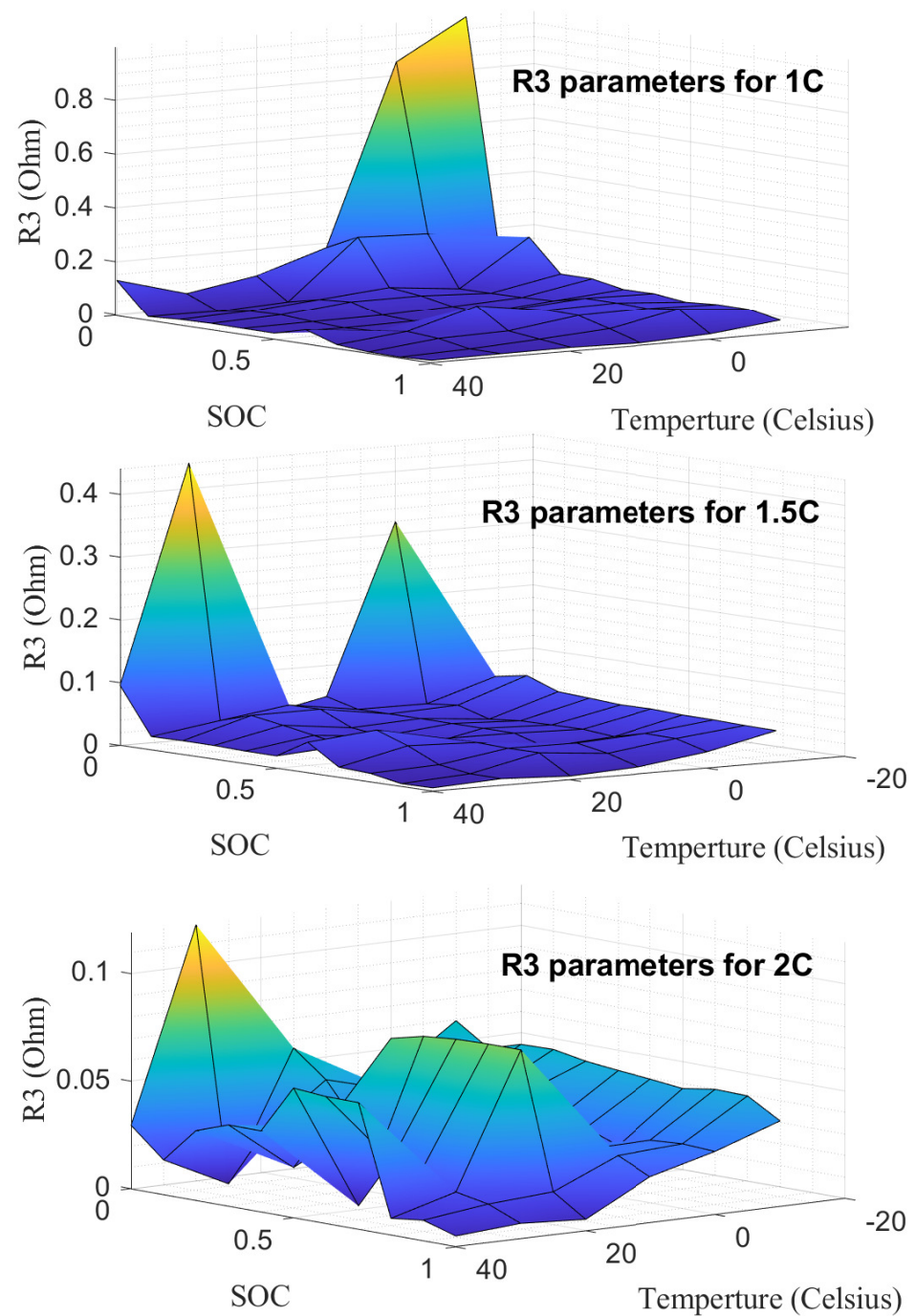


Figure A4. R3 ECM parameters under different C-rate and temperature conditions.

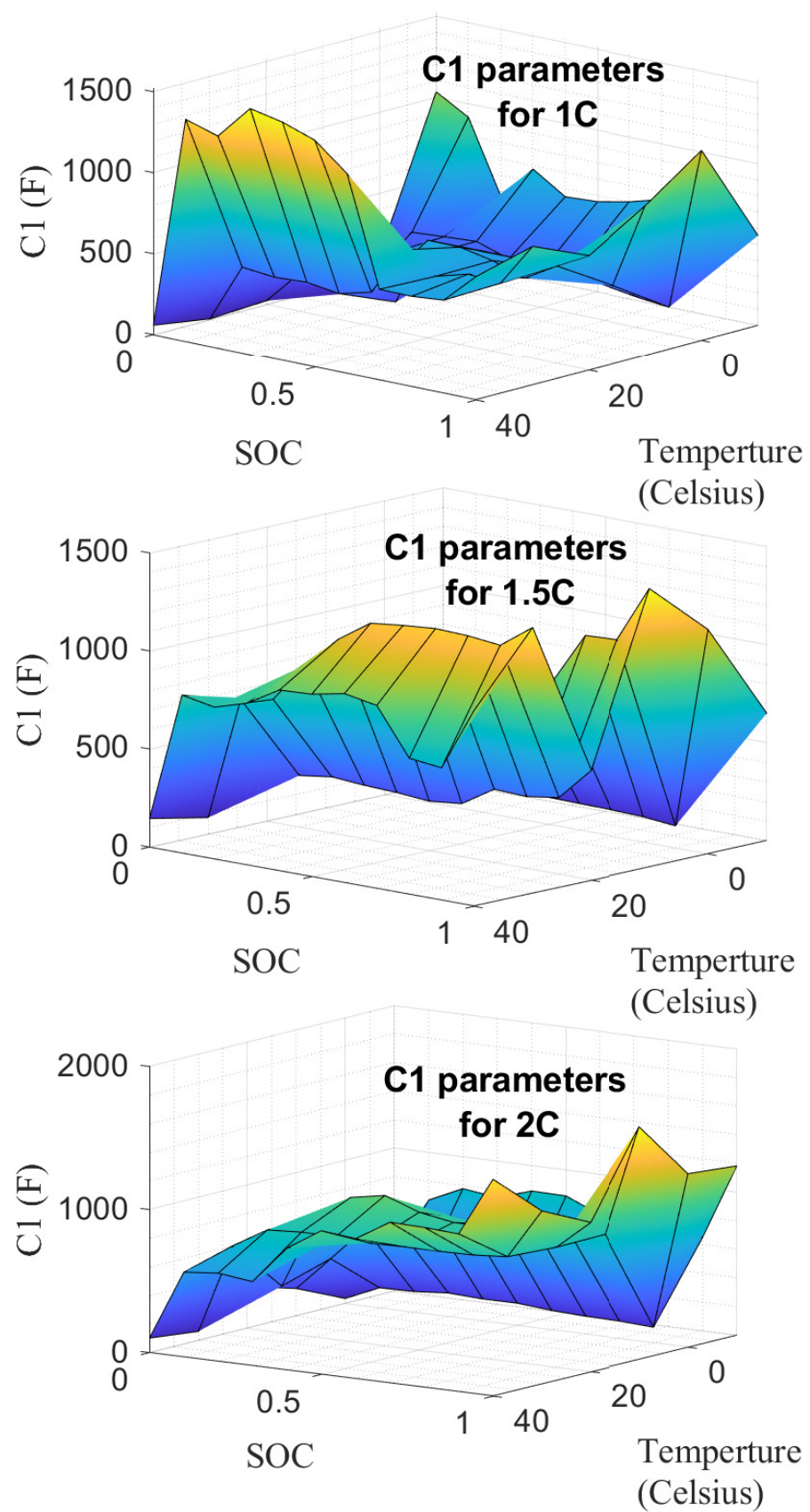


Figure A5. C1 ECM parameters under different C-rate and temperature conditions.

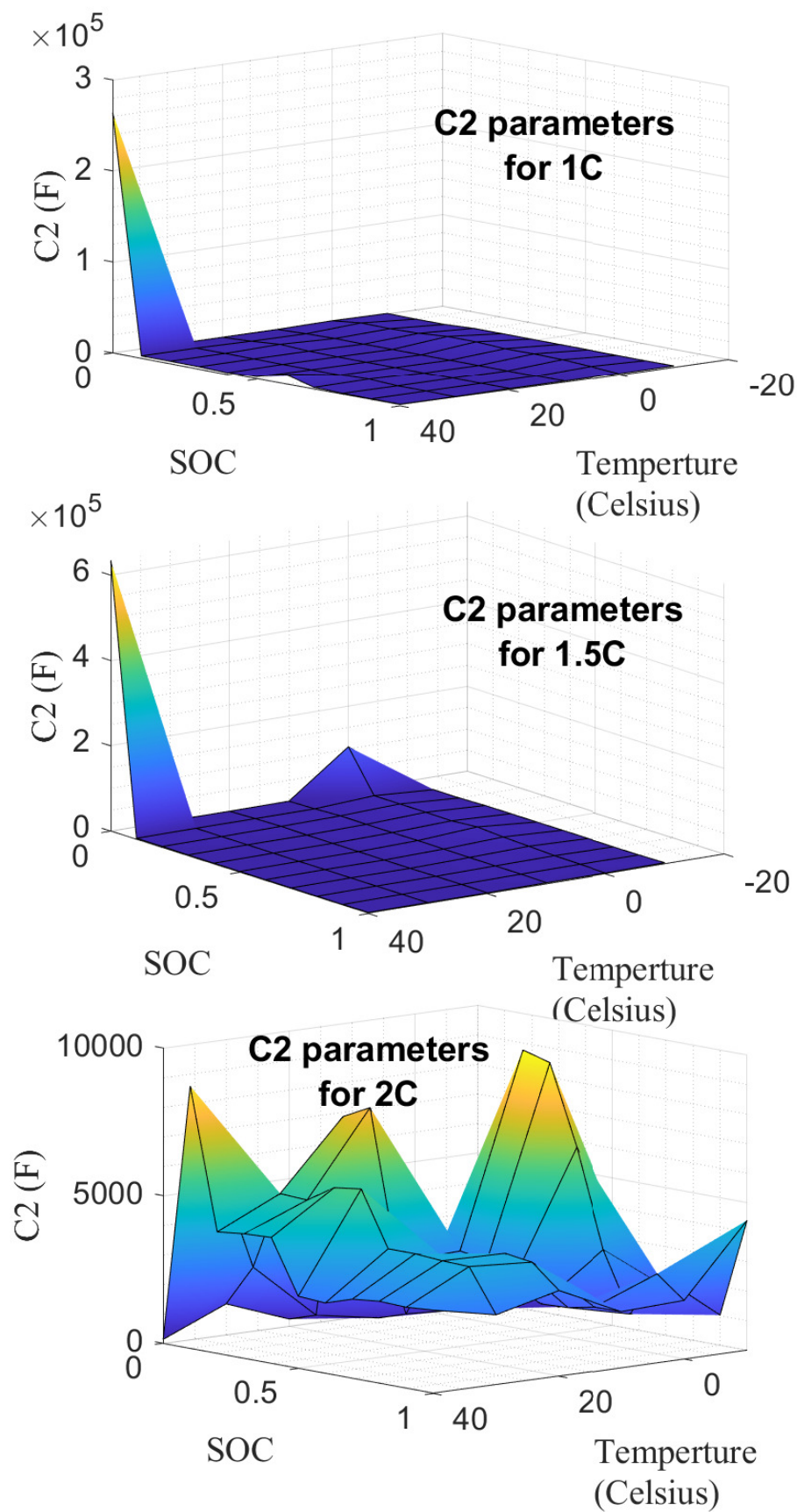


Figure A6. C2 ECM parameters under different C-rate and temperature conditions.

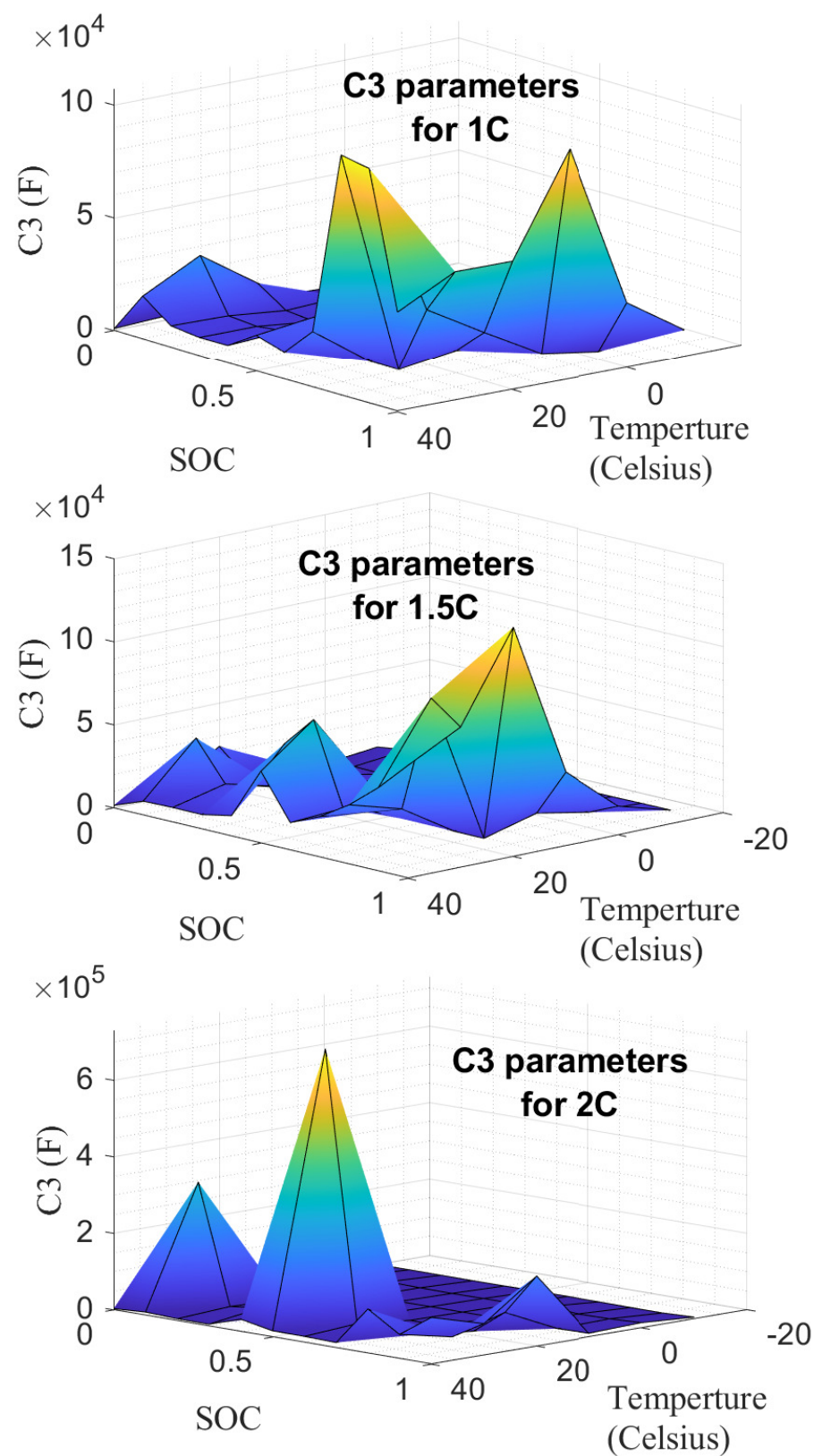


Figure A7. C3 ECM parameters under different C-rate and temperature conditions.

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