Online Reduced Complexity Parameter Estimation Technique for Equivalent Circuit Model of Lithium-ion Battery

Komal Saleem*, Kamyar Mehran*, and Zunaib Ali*.
*School of Electronics Engineering and Computer Science, Queen Mary University of London, UK
Emails: {k.saleem, k.mehran. zunaib.ali}@qmul.ac.uk.

ABSTRACT For control-oriented battery management applications in electric vehicles, Equivalent Circuit Model (ECM) of battery packs offer acceptable modelling accuracy and simple mathematical equations for including the cell parameters. However, in real-time applications, circuit parameters continuously changes by varying operating conditions and state of the battery and thus, require an online parameter estimator. The estimator must update the battery parameters with less computational complexity suitable for real-time processing. This paper presents a novel Online Reduced Complexity (ORC) technique for the online parameter estimation of the ECM. The proposed technique provides significantly less complexity (hence estimation time) compared to the existing technique, but without compromising the accuracy. We use Trust Region Optimization (TRO) based Least Square (LS) method as an updating algorithm in the proposed technique and validate our results experimentally using Nissan Leaf (pouch) cells and with the help of standard vehicular testing cycles, i.e. the Dynamic Driving Cycle (DDC), and the New European Driving Cycle (NEDC).

Key words: Equivalent circuit model, lithium-ion battery, battery management system, parameter estimation, driving cycles, Nissan leaf pouch cell.

1. Introduction

In recent years, energy storage technology has become the centre of focus due to the high power applications in plug-in electric vehicles (PEVs) and government mandates in Europe and UK for the mass adoption of PEVs in the near future [1]. Lithium-Ion Batteries (LiBs) have a dominant role in PEV manufacturing as a main energy source due to their high power density, low Self Discharge (SD) and high energy efficiency [2]. Moreover, other characteristics such as wide operating temperature range [-20°C,+60°C], light weight, small cell size, long life cycle and no residual gas discharge turns LiBs as a suitable candidate for grid side stationary as well as mobile applications [3]. In both scenarios, a Battery Management System (BMS) has the role of performance monitoring and control of LiBs to provide safety and reliability of their operation. However, to carefully investigate the design of a proper BMS, the key element responsible is an efficient and accurate battery model.

Different type of modelling approaches exists to characterize the behaviour of LiB. Among those, pseudo-2-dimensional (P2D) electro-chemical (physics) models offer high accuracy with the cost of high computational time to solve non-linear Partial Differential Equations (PDEs). This rules out P2D models as a candidate for real-time control-oriented applications due to the short and fixed time intervals in processing the information received from the sensors by the control unit, and sending the appropriate commands to the actuators [4]. The battery model is typically resolved within the BMS running on the embedded microcontroller with limited processing capabilities. Using the complex models require more processing time and often result in overflowing the real-time execution for a given sampling rate. Therefore, the sampling rate must be reduced that may, in turn, results in more discretization error and signal inaccuracies [5]. For on-board vehicle processing, Equivalent Circuit Models (ECMs) are good candidate as they offer less computational complexity and ease of implementation with an acceptable accuracy [6, 7]. As a result, ECM has been dominantly used in real-time BMS applications for monitoring and control of battery [8-10].

The ECM uses a series of RC circuits to represent the battery cell/pack dynamics. Adding the RC circuits (levels) may increase the accuracy along with the computational complexity and there must be always a trade-off between them. A number of ECM-type models have been suggested in the literature based on single or multiple RC circuit. The first-order-RC is the simplest topology suggested for ECMs [7]. In [10-12], the parameters of first-order-RC are identified using Recursive Least Square (RLS) and Extended Kalman Filter (EKF). Multiple-RC branch topologies are suggested in the literature by many authors, including the 2nd-order-RC models [13-15] and the 3rd-order-RC models. Even though, the multi-RC models showed better accuracy in approximating the LiB's behaviour using large number of parameters, however, they have a discouraging high computational cost for real-time control applications [7].

After the selection of ECM, estimating and updating the model parameters online is yet a challenging task. Different methods exist in the literature to estimate the battery parameters under different operating conditions. In [16] and [9] sigma point KF and EKF are respectively used to estimate the varying model parameters and states of the battery. Similarly, methods like Generic Algorithm (GA) [17], RLS technique with adaptive multiple forgetting factors [18, 19] and Recursive Extended Least Square (RELS) algorithm [20] are proposed to capture the LiB's parameters. In [21], a novel multi-timescale estimator is developed for the online estimation of battery state and model parameters. All the aforementioned methods provide improved accuracy in estimation; however, they are unable to provide the reduced complexity required for the real-time processing in the BMS. It should be noted that the computational resources of the embedded microcontroller within the BMS are actually limited and thus, the complexity is a critical aspect to be considered for the design and development of estimation algorithms involved in the BMS.

Another concern using ECM is that the battery parameters may vary with changing operating conditions [15, 22, 23]. Thus, battery parameters must be updated based on these variations. A widely-used technique for ECM parameterization is the tabulation of the model parameters under various operating conditions in the form of a look-up table [24, 25]. A numerical parameter estimation technique for pulsating load is proposed in [26, 27]. In [28], the battery parameters are estimated in the form of a look-up table using Lyapunov's direct method and data is obtained for different set of temperature ranges. These methods are frequently used due to the less complexity and acceptable accuracy; however, they require a number of experiments to build up the look-up tables based on different operating conditions. Another drawback of these methods is that the measured data may become obsolete with battery's aging.

In this article, to reduce the complexity and dependency on the look-up tables, an Online Reduced Complexity (ORC) technique is proposed for the online parameter estimation of LiBs. For the analysis and design of the developed technique, parameters are identified using the Trusted Region Optimization (TRO) based Least Square (LS) algorithm for a single-order ECM model. In comparison with the existing methods, the proposed ORC technique is online, has reduced complexity resulting in a considerable reduction in estimation time. The proposed technique is also applied to a second order ECM resulting in a faster estimation compared to existing method. However, it is observed that single-order ECM with proposed ORC technique has much promising results with equivalent accuracy but lower processing time in comparison with higher order ECM. Moreover, reduced order look-up tables are employed to remove the dependency on varying operating conditions due to battery ageing and subsequently, decreases the additional memory units normally used for containing look-up tables. The technique developed in this paper for ECM is generic and applicable to any type of Lithium-ion battery cell. Therefore, by measuring the internal parameters of a cell, the proposed technique can be customised for any manufactured battery cell and is validated by means of real-driving load cycles and experimental laboratory results using Nissan Leaf pouch cell module.

The rest of the paper is organized as follows: the model formulation of LiB is described in Section 2. The design and analysis of the proposed ORC technique along with TRO based LS algorithm is discussed in Section 3. Section IV presents the validation of the proposed technique using the pulsating load and two sets of real world driving cycle data, i.e. the Dynamic Driving Cycle (DDC) and the New European Driving Cycle (NEDC), and experimental hardware test results. Section 5 outlines the benchmarking comparison of existing and proposed techniques for the validation carried out in Section 4. Finally, the paper concludes in Section 6.

2. Equivalent Circuit Modelling of LiBs

The most commonly used ECM model is the Thevenin battery model, where circuit elements (such as resistors, capacitors and dependant voltage source) are used to represent the battery dynamics [29] (see Figure 1). As mentioned in the previous section, adding the number of series RC branches in this type of models in order to increase the accuracy would increase the computational complexity and resulting processing time. In this paper, a single RC Thevenin model is considered for the investigation and design of the proposed ORC technique, as shown in Figure 1.

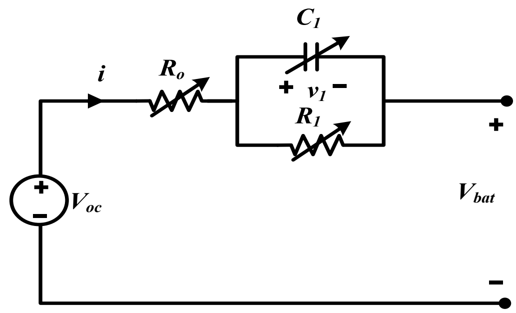


Figure 1. First order Thevenin model of the battery.

In Figure 1, the open circuit voltage V_{oc} is the voltage across the battery terminals under no load condition, and R_o is the internal resistance representing the internal voltage drop when a load is connected to the battery system. Furthermore, the RC branches are responsible for the transient/dynamic behaviour of the battery.

The dynamic mathematical model for an n^{th}-order ECM is shown in (1).

$$\begin{cases} V_{oc}(SoC) = iR_o + \sum_{n=1}^{N} v_n + V_{bat} \\ i = \sum_{n=1}^{N} \left(\frac{v_n}{R_n} + C_n \frac{dv_n}{dt} \right) \end{cases} \tag{1}$$

where, N is the total number of RC branches, $V_{oc}(SoC)$ is the State of Charge (SoC) dependent open circuit voltage, i is the current delivered by the battery, v_n is the voltage across the N^{th} RC branch, and V_{bat} is the battery output voltage.

The control of battery in general is implemented in a discrete domain. Thus, the dynamics of n^{th}-order RC model can be written in an equivalent discretized form using Zero-Order Hold (ZOH), as shown in (2).

$$\begin{bmatrix} v_1(k+1) \\ \vdots \\ v_N(k+1) \end{bmatrix} = \begin{bmatrix} x_1 & & 0 \\ & \ddots & \\ 0 & & x_N \end{bmatrix} \begin{bmatrix} v_1(k) \\ \vdots \\ v_N(k) \end{bmatrix} + \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} i(k) \tag{2}$$

$$\underbrace{V_{oc}(SoC) - V_{bat}}_{V(k)} = R_o i(k) + \sum_{n=1}^{N} v_n(k)$$

where:

$$\begin{cases} x_n = exp\left(-\frac{T_s}{R_n C_n}\right) \\ y_n = R_n(1 - x_n) \end{cases} \tag{3}$$

and T_s is the sampling period, and $i(k)$ is the current at the k^{th} sampling time.

The critical circuit parameters (C_1, R_1, R_0 and V_{oc}) for ECM, in general, are varying and unknown that need to be estimated to allow the high-fidelity approximation of the actual battery behaviour. We propose to use the TRO based LS algorithm for the parameter estimation as will be presented in the subsequent section.

3. THE PROPOSED ONLINE REDUCED COMPLEXITY (ORC) PARAMETER ESTIMATION TECHNIQUE

The proposed technique is designed based on an investigation carried out by analyzing the ECM model for various set of look-up tables associated with each parameter. The investigation considers the size of the table, the required estimation time and the estimation accuracy (measured from the error) as the base for our analysis. Consequently, the single- and multi-order-RC models are tested for various orders of look-up tables that is from 11x1 to 1x1 for each parameter under various type of loading conditions. The load types considered are real-time driving cycles, worst-case pulsating (rectangular/square) load and experimental laboratory test. It has been concluded that the single-RC model with reduced-order 3x1-lookup table has the best results with minimum estimation time and error for pulsating load. Whereas a single value (1x1 look-table) of each parameter is sufficient to accurately estimate the LiB parameters for practical driving cycles and laboratory results, with minimum estimation time and without compromising the estimation accuracy. Thus, equivalent accuracy can be achieved by selecting less number of parametric values (related to each parameter) in comparison with the existing technique using look-up tables [26]. This results in the preposition of our proposed Online Reduced Complexity (ORC) technique which considers less number of parametric values (3x1 or 1x1 lookup tables for each parameter) to achieve similar accuracy with reduced complexity and lower processing time. In addition, due to reduction in the order of lookup tables, the need for more memory units is also reduced.

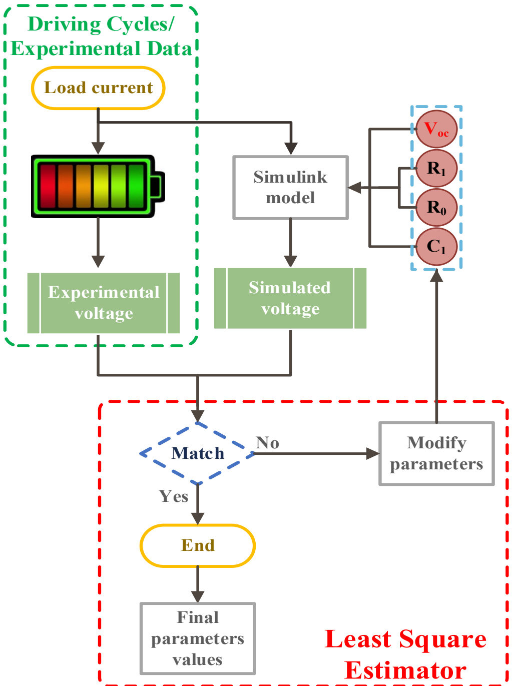


Figure 2. Flow diagram of the parameter estimation process.

A TRO based LS algorithm has been developed to estimate the parameters of the proposed ORC technique. The parameter estimation is carried out by comparing the simulated data (output voltage of the designed simulated model) with a set of experimental data (output voltage of the practical battery), as depicted in Figure 2. The load current and voltage datasets are obtained from real-world driving cycles and the experimental laboratory measurements. The same load (current profile) is also provided to the simulation setup in order to calculate the simulated terminal voltage and execute the estimation process. The parameters are estimated and error (between the output voltage of hardware and simulation setup) is minimised.

In the estimation procedure, the parameters are updated at each iteration and error is minimized between the simulated and the experimental output voltage. The estimator minimizes the error based on a predefined threshold and the procedure ends when the error goes below the threshold limit (0.001 V) or when the difference of the two successive iterations becomes zero. The TRO based LS algorithm developed for the parameter estimation of a single-order ECM is presented below.

The z-transformation of (2) yields the following transfer function:

$$H(z) = \frac{V(k)}{I(k)} = R_o + \frac{y_1}{z - x_1} + \frac{y_2}{z - x_2} + \cdots + \frac{y_N}{z - x_N} \tag{4}$$

where,

$$V(k) = V_{oc}(SoC) - V_{bat} \tag{5}$$

Rearranging (4) as:

$$V_{oc}(SoC) - V_{bat}[1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_n z^{-N}] = I(k)[b_o + b_1 z^{-1} + b_2 z^{-2} + \cdots + b_n z^{-N}] \tag{6}$$

Equation (6) can be rewritten as (7)

$$V_{oc}(k) - V_{bat}(k) + a_1\big(V_{oc}(k-1) - V_{bat}(k-1)\big) + \cdots a_N\big(V_{oc}(k-N) - V_{bat}(k-N)\big) = b_o\, I(k) + b_1\, I(k-1) + \cdots b_N\, I(k-N) \tag{7}$$

Rearranging (7) as:

$$V_{bat}(k) = V_{oc}(k) + a_1\big(V_{oc}(k-1) - V_{bat}(k-1)\big) + \cdots a_N\big(V_{oc}(k-N) - V_{bat}(k-N)\big) - b_o\, I(k) - b_1\, I(k-1) - \cdots b_N\, I(k-N) \tag{8}$$

All the coefficients in (8) are the function of circuit parameters that are continuously updating.

Therefore, (8) can be rewritten as the following Least Square regression form [30].

$$y(k) = \theta\varphi(k) \tag{9}$$

where, θ and $\varphi(k)$ given in (10) and (11) are respectively the parameter vector and the regressor.

$$\theta = [V_{oc}(k)\ a_1 \ldots a_N\ \ b_o\ \ b_1 \ldots b_N] = \mathcal{F}(SoC, C_1, \ldots, C_N, R_o, \ldots, R_N) \tag{10}$$

$$\varphi(k) = [1 + V(k-1) \ldots + V(k-N) - I(k)\ - I(k-1) \ldots - I(k-N)]^T \tag{11}$$

$$y(k) = V_{bat} \tag{12}$$

The LS parameter identification described above is for the n^{th}-order ECM model. However, for a single-order ECM (in this paper), the parametric coefficients are characterised in the following equations:

$$\begin{cases} a_1 = -x_1 = exp\left(-\frac{T_s}{R_1 C_1}\right) \\ b_o = R_o \\ b_1 = -R_o x_1 + y_1 \\ = -R_o exp\left(-\frac{T_s}{R_1 C_1}\right) + R_1\left(1 - exp\left(-\frac{T_s}{R_1 C_1}\right)\right) \end{cases} \tag{13}$$

The battery's terminal voltage V_{bat} and load current I are known. On the other hand, the open circuit voltage $V_{oc} = \mathcal{F}(SoC)$ (which is actually the function of battery's state of charge, SoC) and the electrical parameters of circuit are unknown. Hence, TRO based LS algorithm is used to obtain the unknowns by online parameter estimation.

The parameter vector θ is estimated by minimizing the following cost function.

$$W_{LS}(\hat{\theta}) = \sum_{j=1}^{k}\left[y(k) - \hat{\theta}\varphi(k)\right]^2 \tag{14}$$

Thus, based on LS, the estimated vector $(\hat{\theta})$ is obtained by minimizing $W_{LS}(\hat{\theta})$ as:

$$\frac{\partial W_{LS}(\hat{\theta})}{\partial\hat{\theta}} = \left[\left(y(k) - \hat{\theta}\varphi(k)\right)^T\left(y(k) - \hat{\theta}\varphi(k)\right)\right] = 0 \Rightarrow \hat{\theta} = [\varphi^T\varphi]^{-1}\varphi^T y \tag{15}$$

The estimated vector $\hat{\theta}$ in (15) provides a unique solution for linear least square problems. However, battery model whose parameters needs to be estimated are non-linear in nature, thus require using iterative method. Consequently, the least square, in this paper, is augmented by a trust region optimization algorithm to achieve a better and faster convergence.

The stepwise execution of the TRO based LS on the ECM is detailed as below:

Step 1: Measure the battery's load current (input) and terminal voltage (desired output) for k^{th} sampling time.

Step 2: Take an initial point θ such that $\theta \in \aleph$-space. The objective is to update θ such that the cost function is minimized. The TRO defines a two-dimensional subspace $\jmath$ around θ and approximate the cost function in this region by taking the first two terms of Taylor series expansion as:

$$\widetilde{w}_{LS} = \left\{\tfrac{1}{2}s^T H s + s^T\nabla \quad s \in \jmath\right\} \tag{16}$$

where, H represents the Hessian matrix and ∇ is the gradient of W_{LS} at the current point θ.

Step 3: The approximate function $(\widetilde{w}_{LS})$ is minimized for a trial step s within the $\jmath$-subspace as:

$$\underbrace{min}_{s}\{\widetilde{w}_{LS}\} \Leftrightarrow \underbrace{min}_{s}\left\{\tfrac{1}{2}s^T H s + s^T\nabla \quad s \in \jmath\right\} \tag{17}$$

The approximation approach used in the TRO restricts the sub-problem of trust region to a two-dimensional (2D) space $\jmath$ and the solution to (17) comes out as trivial. The 2D subspace is formed by spanning s_1 and s_2 over a linear space.

The s_1 follows the gradient direction, whereas s_2 is an approximate Newton direction given by solution to $H.s_2 = -\nabla$. The main objective in selecting the 2D space ɲ is to achieve a global convergence using gradient direction and thus, attaining a faster local convergence via the Newton based trial step s.

Consequently, the solution to (17) is obtained using the Quadratic Programming (QP) algorithm, which result in an optimal trial step s that minimizes the quadratic function $\widetilde{w}_{LS}$ such that $s \in$ ɲ.

Step 4: Subsequently, if $f(\theta + s) < f(\theta)$, update the current point as $\theta = \theta + s$ and go to step 5. Otherwise, the initial θ remains unchanged, the size of trust region is shrunk and step 3 is repeated.

Step 5: Calculate the error based on updated θ. If the error is not minimized to the pre-defined value, update the trust region dimensions and repeat the iteration by going to step 3.

Step 6: Stop the algorithm if cost function reaches to pre-defined threshold value and calculate the final model parameters using (13).

Step 7: Calculate the SoC of LiB by using Coulomb Counting (CC) method, given in (18).

$$SoC(k) = SoC(k-1) - \frac{T_s}{Q_n}\sum_{0}^{k}(\eta * i(k) - D_s) \qquad (18)$$

where Q_n is the battery's nominal capacity, η is the Coulombic efficiency, and D_s is the self-discharging rate of the LiB. Ideally, the value of self-discharge is zero, which shows that the Coulombic efficiency is 100%. The typical value of LiBs self-discharge is between 2% to 3% per month [31]. Thus, in this paper, D_s and η are respectively assumed as 0 and 1.

The main problem associated with the parameter estimation of a single cell model in [26] using lookup table is estimating large number of parametric values (11x4=44) which actually increases the complexity and calculation time. Consequently, in LiB packs where a large number of cells connected in series and parallel, the computational complexity and the resulting response time will be increased to a greater extend, making it impractical for real-time control applications. In the proposed ORC technique, we substantially reduce the online estimation time by reducing the number of parametric values without compromising the estimation accuracy.

4. Results and Discussion

To provide a good comparison with the existing results in [26], we first present the analysis for square/rectangular type discharging load pulse. Following this, Dynamic Driving Cycle (DDC) and New European Driving Cycle (NEDC) waveforms are used to verify the effectiveness and advanced performance of the proposed technique under standard driving cycles. Finally, the proposed technique is validated using practical laboratory results.

4.1. Simulation results for pulsating discharging pulses

The proposed ORC parameter estimation technique is first applied to the pulsating load similar to the one used in [26]. The constant magnitude load pulses are considered in the first half of the load cycle (as used in [26]) and variable load pulses in the rest in order to investigate the performance of proposed technique under fixed and variable pulse magnitude. The single order-RC model is tested for various orders of look-up table that is from 11x1 to 2x1 for each parameter, and it has been concluded that the reduced order 3x1-lookup table presents best results with minimum estimation time and error. Consequently, Figure 3 presents and compares the results of the proposed ORC technique with the method discussed in [26]. The (3x4) and (11x4) in Figure 3 respectively refers to the results for the proposed ORC technique and the method in [26].

Figure 3 shows that there is no significant difference in the estimated output voltage waveforms either by estimating 44 or 12 parametric values (that is 11x1 or 3x1 lookup tables of each parameter for the existing and the proposed technique, respectively). It can also be seen from the error subplot that the difference between measured and simulated voltage for both proposed and existing techniques is negligible. The time taken to estimate 44 parameters is 8 min 25 s, whereas for estimating 12 parameters, the proposed technique takes 2 min and 35 s only, as shown in Table 1. The 11x4 parametric values minimized the sum of squared error to 9.8966×10^{-4}%. On the other hand, the method with 3x4 parameters minimizes the sum of squared error to 6.4×10^{-3}%. It is worth mentioning that the relative error is the difference between the last two iterations, and the maximum error is the value of cost function at iteration zero.

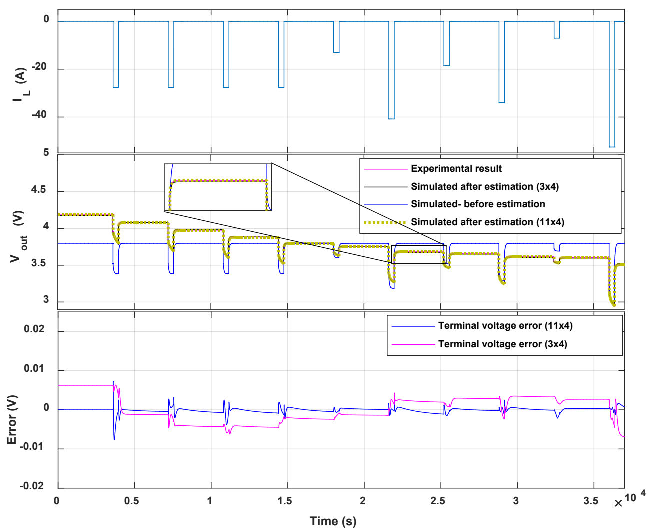


Figure 3. Estimation results of the proposed ORC technique and the existing method [26].

The trajectories of estimated parameters during each iteration for existing and proposed technique are shown in Figure 4 and Figure 5, respectively. For the proposed case, 3 parametric values for each parameter are updated after each iteration. However, on the other hand, the existing technique requires 11 parametric values to be estimated for each parameter.

It can be observed that the estimation presented by the proposed ORC technique is approximately equal to the existing estimation method with significant reduction in complexity and computational burden. Almost 70% reduction is observed in the overall estimation time of the proposed technique with performance equivalent to the existing method. Thus, the proposed ORC technique is able to replace the existing methods for a less-complex and faster estimation, but without compromising the accuracy of the results.

Table 1: The estimation progress status of the existing and the proposed techniques for pulsating load.

Existing method [26] (44 parametric values)					
Iterations	0	1	2	3	4
Cost function error (%)	2.5341	0.1485	0.0046	4.020×10^{-4}	9.896×10^{-4}
Relative error (%)	5.87×10^{-4}				
Estimation time	8 min 25 s				
Proposed ORC Technique (4 parametric values)					
Iterations	0	1	2	3	4
Cost function error (%)	2.2541	0.1723	1×10^{-2}	6.3×10^{-3}	6.4×10^{-3}
Relative error (%)	1.62×10^{-4}				
Estimation time	2 min 35 s				

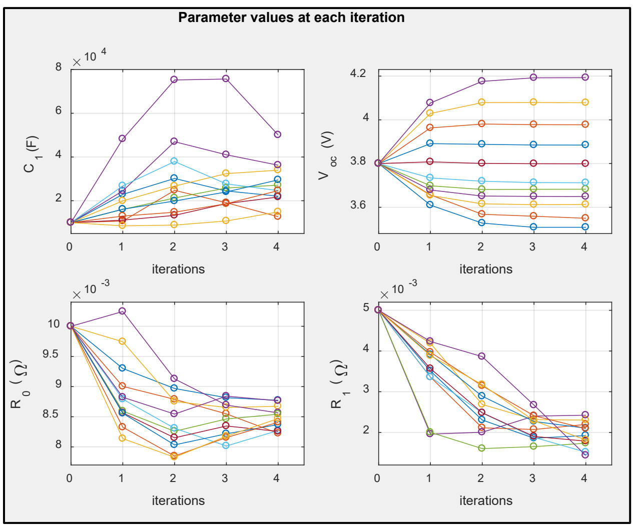


Figure 4. The parameter values at each iteration of the existing method for the pulsating load. Note: The trajectories in each subplot refer to values of a single parameter, and the corresponding parameter is specified on the y-axis

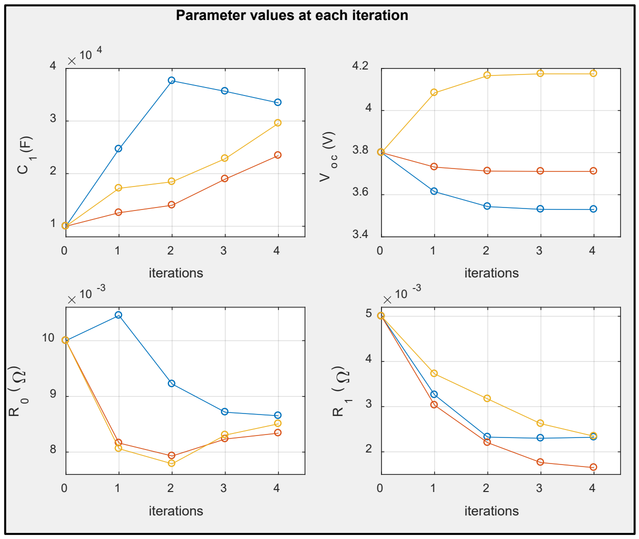


Figure 5. The parameter values at each iteration of the proposed technique for the pulsating load. Note: The trajectories in each subplot refer to values of a single parameter, and the corresponding parameter is specified on the y-axis.

4.2. Validation of the proposed ORC technique using realistic driving cycles

To validate the proposed technique for ECM, we use standard real-world driving cycles which accurately emulate the behaviour of an electric vehicle for a given driving load in real environment. This has become a common approach to check the validity of the new algorithms developed for ECMs.

A driving cycle is a series of data points representing the speed of a vehicle with respect to the time. The driving cycles are produced by different countries and organizations to assess the performance of vehicles in various ways. The testing companies usually provide corresponding speed, battery voltage and current waveforms for such standard driving cycles and are easily available in the literature [32]. Hence, the proposed ORC technique is tested for DDC and NEDC waveforms in order to validate its advanced performance under practical standard driving cycles.

4.2.1. Dynamic Driving Cycle (DDC)

In the dynamic driving cycle, the vehicle tends to move on a road having rough surface. The speed of the vehicle fluctuates too much so as the load on the battery used in the electric vehicle. The load profile of such driving cycle with regenerative braking system is shown in Figure 6. For such a load, the terminal voltage (with and without estimation) for both proposed and existing method of [26] is also depicted in Figure 6.

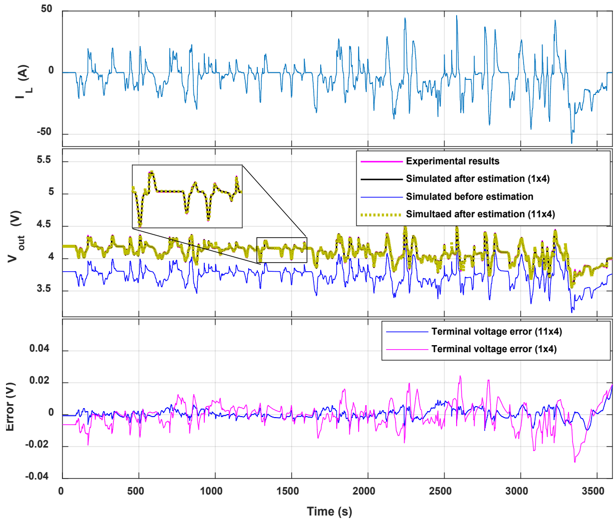


Figure 6. Before and after estimation results of the existing and the proposed ORC techniques under the DDC.

Table 2: The estimation progress status of the existing and the proposed techniques for the DDC load.

Existing method [26] (44 parametric values)									
Iterations	0	1	2	3	4	5	6		
Cost function error (%)	360.36	18.853	0.3349	0.1291	0.1099	0.1061	0.1060		
Relative error (%)	1.38×10^{-4}								
Estimation time	17 min 21 s								
Proposed ORC Technique (4 parametric values)									
Iterations	0	1	2	3	4	5	6	7	8
Cost function error (%)	360.439	21.4802	3.5870	1.7265	0.6694	0.3133	0.2795	0.2738	0.2731
Relative error (%)	5.7×10^{-4}								
Estimation time	1 min 26 s								

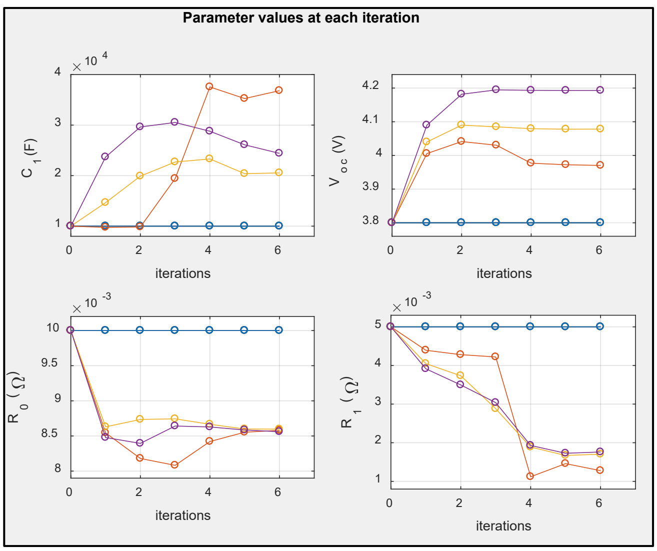


Figure 7. The parameter values at each iteration of the existing method for the DDC.

For DDC, the ECM model is tested for various orders of look-up tables staring from 11x1 to 1x1, and it is observed that the 1x1-lookup table has best results with minimum estimation time and error. This means a single value of each parameter is enough to estimate for this practical load. The corresponding trajectories of the estimated parameters at each iteration for the existing method of [26] and proposed ORC technique are depicted in Figure 7 and Figure 8, respectively. It is clear from Figure 8 that only single value of each parameter is updated at each iteration, which actually contributes to promising reduction of complexity and estimation time.

It can be seen from the terminal voltage and error response of Figure 6 that there is no significant difference between the results for model estimated using 44 parameters (11x4 lookup tables) and 4 parameters (1x4 lookup tables). The time taken to estimate 44 parameters is 17 min 21 s. Whereas, a time of 1 min 26 s is required to estimate single value of the 4 parameters, as shown in Table 2. The 11x4 parameters minimized the sum of squared error to 0.1060%. On the other hand, the 1x4 parameters minimize the sum of squared error to 0.2731%.

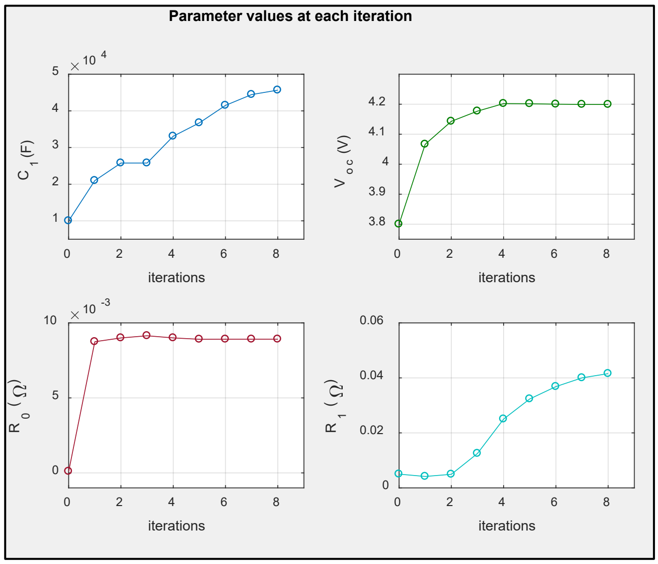


Figure 8. The parameter values at each iteration of the proposed technique for the DDC.

The results show that the proposed technique has similar estimation performance with reduced computational burden when compared to method in [26]. It requires less estimation time and a few number of parametric values to be estimated while maintaining the estimation accuracy, as shown in second subplot of Figure 6.

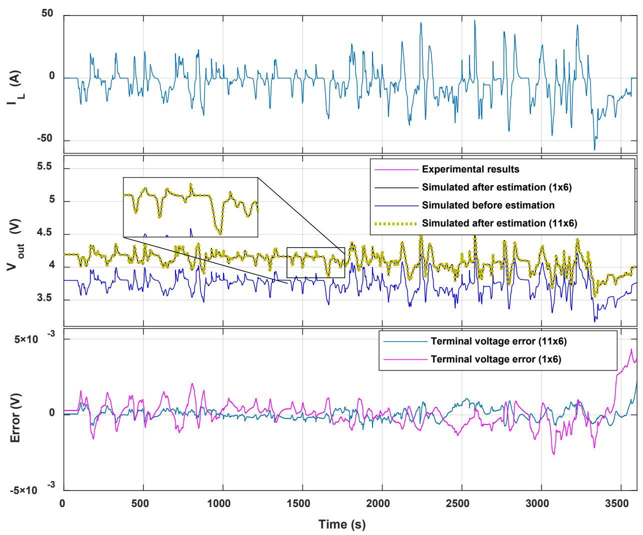


Figure 9. Before and after estimation results of the existing and the proposed ORC techniques under the second-order DDC.

The proposed ORC technique is also implemented on a second-order RC circuit for a DDC as shown in Figure 9 and results are compared to the existing method presented in [26] and single-order RC circuit. Comparing the proposed ORC technique for the first and second order ECM (Figure 6 and Figure 9) shows that there is no significant difference in the output voltage estimation results for both type of circuits. However, with equivalent estimation results, the proposed technique with second-order RC requires 1 min and 13 s more estimation time comparing to the single-order RC (see Table 2 and Table 3). Hence, it would be logical for us to use single-order RC circuit in this study. Furthermore, as can be seen (Table 3), compared to the existing method, the proposed technique requires 94.5% less estimation time.

Table 3: The estimation progress status of the existing and the proposed techniques for the second-order DDC load.

Existing method [26] (66 parametric values)											
Iterations	0	1	2	3	4	5	6	7	8	9	10
Cost function error (%)	410.366	23.1275	0.6106	0.2158	0.1346	0.1346	0.1253	0.1091	0.1071	0.1071	0.1067
Relative error (%)	2.86×10^{-4}										
Estimation time	48 min 18 s										
Proposed ORC Technique (6 parametric values)											
Iterations	0	1	2	3	4	5	6	7	8	9	
Cost function error (%)	419.719	32.0657	6.3457	3.2233	1.2840	0.3301	0.1231	0.1085	0.1085	0.1084	
Relative error (%)	9.08×10^{-5}										
Estimation time	2 min 39 s										

4.2.2. New European Driving Cycle (NEDC)

The NEDC is supposed to represent the typical usage of a car in Europe [33]. The voltage and current curves for NEDC during battery discharge are presented in the Figure 10. Initially the battery was fully charged and then discharged to 89%.

The NE driving cycle is applied to both proposed and existing estimation methods, and results are depicted in Figure 10. The estimation carried out by the existing method is accurate enough that it reduces cost function error from 153.6384% to 6.5×10^{-3}%. The relative error between the two successive iterations in this case is 6.62×10^{-4}%. However, it takes 6 iterations to estimate the 11x4=44 parametric values within the estimation time of 33 min 39 s, (see Table 4).

On the other hand, the proposed technique requires 2 min 38 s to estimate the parameters, which is far less than the time taken by the existing method. From the results in Figure 10, it can be observed that there is no significant difference in the estimated waveforms for both methods, except that the proposed one requires less computational resources. The sum of squared error and relative error are respectively reduced to 1.1×10^{-2} and 9.15×10^{-4} in less time when compared to the existing method. Hence, it can be concluded that the proposed method shows good performance in terms of accuracy with reduced estimation time and computational complexity without compromising on the error.

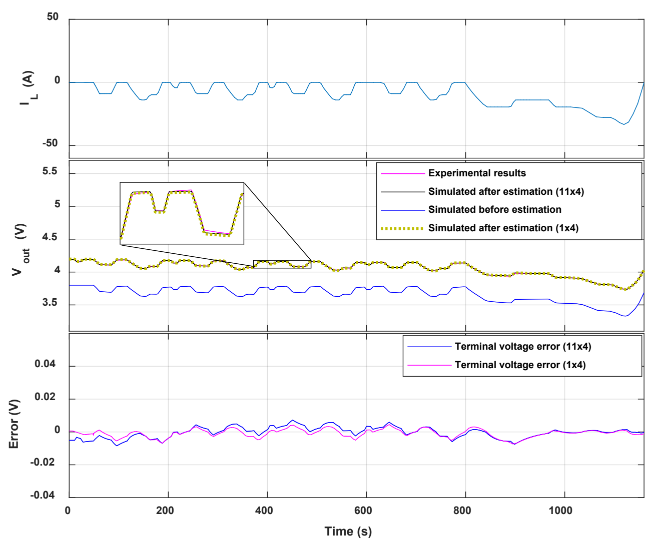


Figure 10. Before and after estimation results of the existing and the proposed ORC technique for NEDC.

The corresponding trajectories of updated parameters for both proposed and existing methods are shown in Figure 12 and Figure 11, respectively. The reduction in number of parametric values to 1 for each parameter in the proposed technique actually contributes to lower computations and faster estimation.

Table 4: The estimation progress status of the existing and the proposed technique for NEDC load.

Existing method [26] (44 parametric values)								
Iterations	0	1	2	3	4	5	6	
Cost function error (%)	153.6384	9.5040	0.1399	9.8×10^{-3}	7.1×10^{-3}	7.1×10^{-3}	6.5×10^{-3}	
Relative error (%)	6.62×10^{-4}							
Estimation time	33 min 39 s							
Proposed ORC Technique (4 parametric values)								
Iterations	0	1	2	3	4	5	6	7
Cost function error (%)	153.6385	9.7711	0.4340	8.32×10^{-2}	2.9×10^{-2}	1.53×10^{-2}	1.19×10^{-2}	1.1×10^{-2}
Relative error (%)	9.15×10^{-4}							
Estimation time	2 min 38 s							

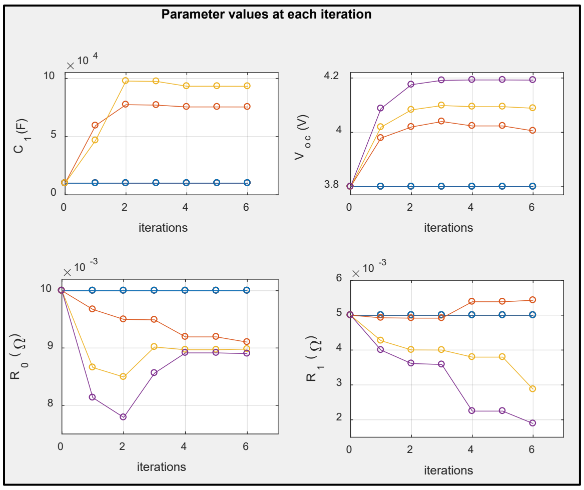


Figure 11. The parameter values at each iteration of the existing method for the NEDC.

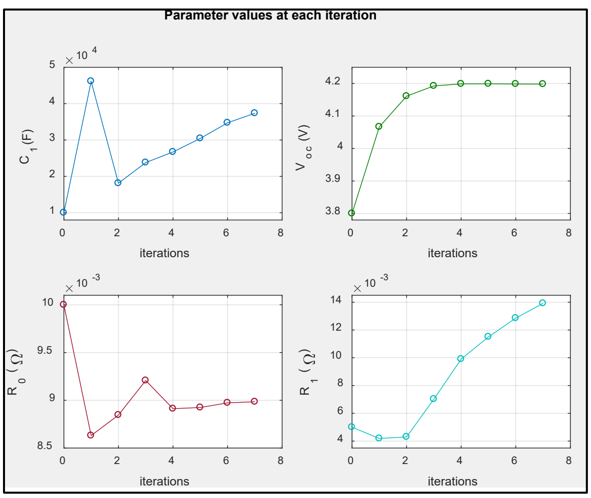


Figure 12. The parameter values at each iteration of the proposed technique for the NEDC.

4.3. EXPERIMENTAL RESULTS

The experimental laboratory setup is shown in Figure 14. The test bed includes a second generation Nissan Leaf pouch Lithium-ion battery module. The battery consists of 4 cells (2 in series, 2 in parallel). The rated capacity of each cell is 33.1Ah, which consist of $LiMn_2O_4/LiNiO_2$ cathode and graphite anode. The Neware battery testing unit BTS 4000 5V/20A comprising of a testing equipment and a control unit is an eight channel device, which is used to generate different charging/discharging load cycles for the battery. The dSPACE MicroLabBox DS-1202 is used to record the load current and output voltage waveform of the battery. The recorded data is then processed by Matlab/Simulink estimation model for online parameter estimation of the battery ECM. This is achieved by minimizing the error between the terminal voltage of Nissan leaf battery and simulated equivalent electrical model.

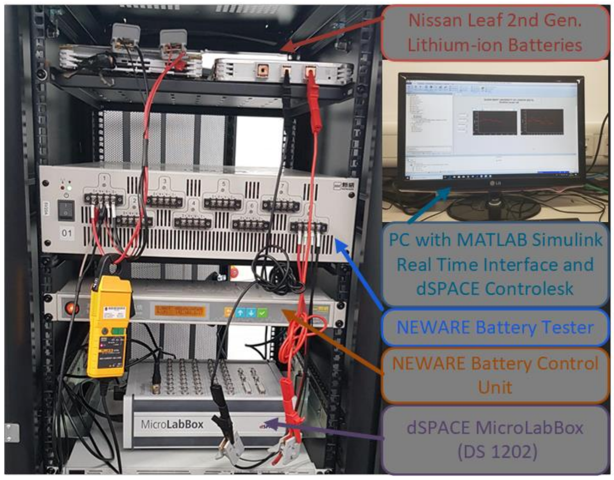


Figure 13. Experimental setup.

In the online estimation process, the load waveform and its corresponding output voltage is recorded for every 600 s and given as input to the ORC parameter estimation model. Subsequently, the model estimate and update the parameters by minimising the error between the output voltage of the experimental recorded data and simulated model. Thus, the model parameters are updated after every 600 s by repeating the online estimation process for a new set of data. The five different load cycles and their corresponding waveforms taken for every 600 s are shown in Figure 14. The experimental results are analysed using both existing technique and proposed reduced complexity technique. It can be seen from Figure 14 that the proposed technique estimates the parameters with less time in comparison to the existing technique without compromising on the accuracy. There is almost no difference between the voltage waveform estimated using 44 parameters (11x4 look-up tables) and 4 parameters (1x4 values). The time taken by existing technique to estimate the desired experimental voltage waveform for load 1 to 5 is 20 min 12 s, 14 min 16 s, 18 min 30 s, 29 min 39 s and 34 min

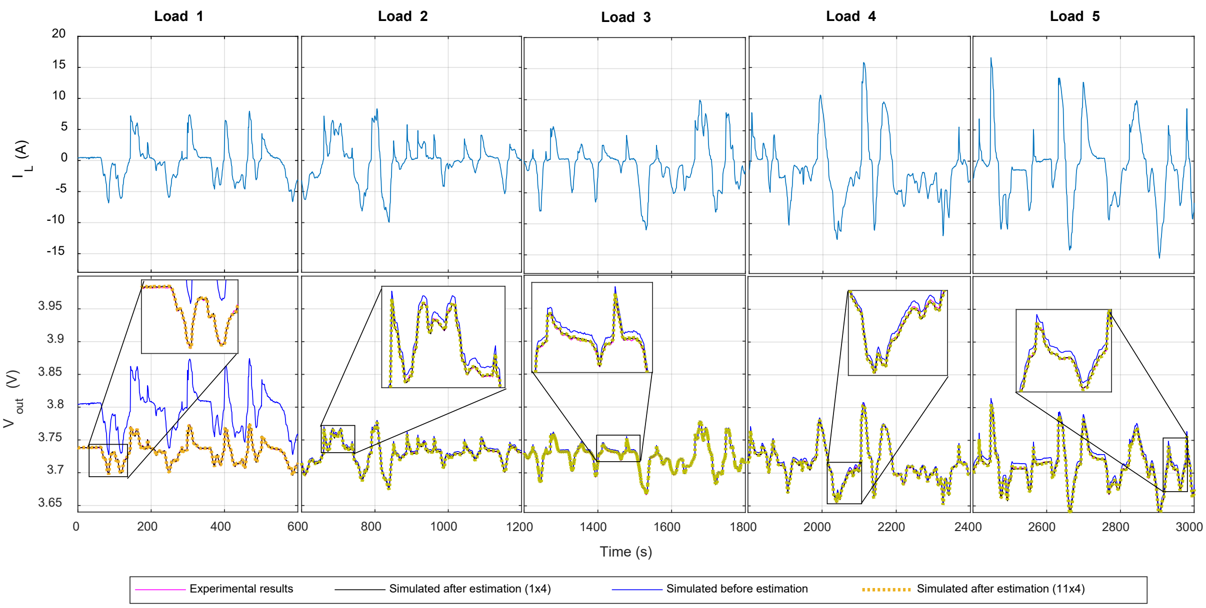


Figure 14. Experimental validation of the proposed ORC technique using NEWARE battery cycler, Nissan Pouch cell battery and MATLAB-dSPACE control desk.

Table 5: The estimation progress status of the existing and the proposed techniques for the experimental results.

		Load 1: 1:600 s	Load 2: 600:1200 s	Load 3: 1200:1800 s	Load 4: 1800:2400 s	Load 5: 2400:3000 s
Existing method [26]	Iterations	0 1 2 3 4 5	0 1 2 3	0 1 2 3 4	0 1 2 3 4 5	0 1 2 3 4 5 6 7 8
	Cost function error (%)	180.2281 2.4995 0.1795 0.1217 0.1201 0.1193	0.5444 0.1399 0.1399 0.1389	0.3660 0.1442 0.1442 0.1442 0.1438	5.3748 0.4865 0.2236 0.2212 0.2212 0.2208	4.2984 0.3678 0.3678 0.3611 0.3577 0.3520 0.3469 0.3442 0.3437
	Relative error (%)	7.62×10^{-4}	9.21×10^{-4}	3.05×10^{-4}	2.06×10^{-4}	3.86×10^{-4}
	Estimation time	20 min 12 s	14 min 16 s	18 min 29 s	29 min 39 s	34 min 27 s
Proposed ORC	Iterations	0 1 2 3 4 5	0 1 2	0 1 2 3 4 5	0 1 2 3 4 5 6	0 1 2 3 4
	Cost function error (%)	180.2281 2.4634 0.1894 0.1232 0.1201 0.1191	0.5659 0.1378 0.1375	0.3376 0.1928 0.1511 0.1438 0.1438 0.1428	1.6884 0.4741 0.2608 0.2251 0.2159 0.2138 0.2135	2.3991 0.3410 0.3295 0.3276 0.3274
	Relative error (%)	9.12×10^{-4}	2.49×10^{-4}	9.02×10^{-4}	2.43×10^{-4}	2.03×10^{-4}
	Estimation time	0 min 46 s	0 min 58 s	2 min 3 s	2 min 34 s	1 min 49 s

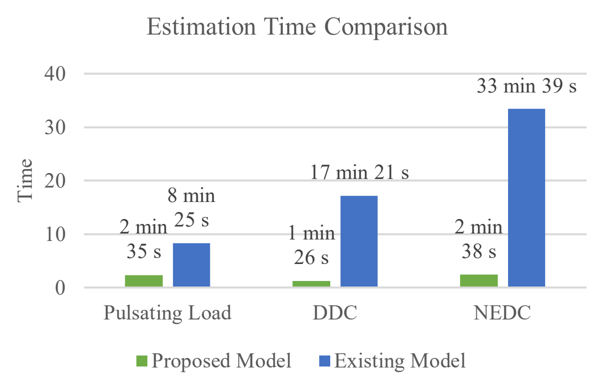
27 s, respectively (see Table 5). The time taken is far more than the recording period of 600 s or 10 minutes. In other words, the time taken by the existing technique to estimate the parameters is such a high value that in meanwhile 3 more cycles become ready for the repeating process of estimation. Hence, the existing technique is not suitable for real-time estimation. On the other hand, the time taken by the proposed reduced complexity technique for load 1 to 5 is 0 min 46 s, 0 min 58 s, 2 min 3 s, 2 min 34 s and 1 min 49 s, respectively (see Table 5). The time taken by the proposed technique is considerably less and a practical solution to EVs. By comparing the error at last-iteration for each load of proposed and existing technique, it can be seen that accuracy is not compromised in the proposed method. Hence, it is validated that the proposed ORC technique can estimate parameters online without compromising on accuracy and with reduced complexity in comparison with the existing technique.

In real-time, the proposed technique will run in parallel with the electric vehicles, receives the terminal voltage and current with a specific sampling time, and predicts the internal parameters of battery (used in the vehicle). Consequently, the resulting estimated model (which keep on updating itself based on new samples) is used by battery management system for the control and management purposes of the battery.

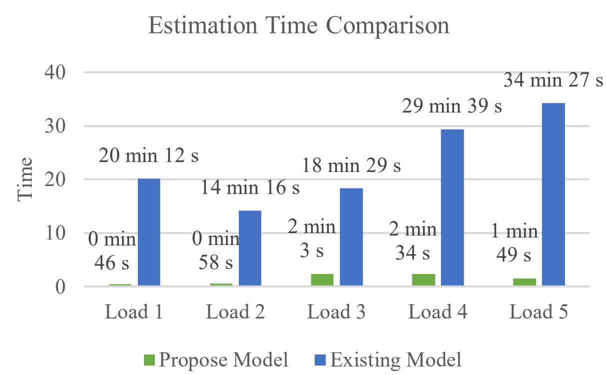
5. Comparison

A comparison of estimation time is established for single-RC ECM under various type of loads, i.e. pulsating load, driving cycles and experimental load cycles (see Figure 15 (a) and (b)). It can be seen that for all type of loads, the proposed approach requires significantly less time for online estimation comparing to the existing method with equivalent performance in terms of estimation. For pulsating load, DDC and NEDC, the proposed technique respectively requires 70%, 91.7% and 92.1% less processing time when compared to the existing one. Furthremore, the experimental results in Figure 15 (b) also show that the proposed technique for load 1 to 5 respectively takes 96.2%, 93.2%, 88.9%, 91.3% and 94.7% less estimation time as compared to the existing one. This makes the proposed technique a good candidate for real time applications (such as EVs).

A comparison is also established between the number of parametric values vs. the estimation time as well as the Sum Square Error (SSE) for DDC (see Figure 16). The line graph shows that the estimation time is reduced by decreasing the parametric values but without compromising the accuracy. From this step wise evaluation (11x4 to 1x4), the single value for each parameter requires least estimation time. On the other hand, the bar chart graph in Figure 16 quantifies the SSE of the terminal voltage, showing that the maximum error for minimum number of parameters is 0.2731%. Hence, in the proposed technique the complexity and estimation time is reduced without compromising on accuracy, i.e. estimation error, as shown graphically in Figure 16.



(a)



(b)

Figure 15. The estimation time comparison chart between the existing and the proposed technique of (a) pulsating load and driving cycles (b) experimental load cycles.

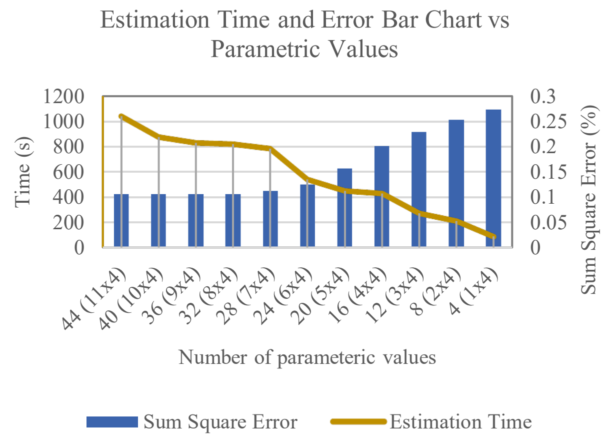


Figure 16. Reduction in estimation time and error bar chart with decrease in number of parametric values.

6. Conclusions

The electric circuit modelling of Lithium-ion batteries is widely used for real-time BMS applications. The model parameters in an ECM are purely dependant on the operating conditions. So, for real-time operation, they need to be estimated and updated online to hold the modelling accuracy. The computational complexity is a critical aspect in the design and development of estimation algorithms for BMS due to the limited computational resources of the embedded microcontrollers. We proposed a novel ORC technique for the estimation of battery's circuit parameters, which is computationally less complex, easy to implement and accurate, and requires less estimation time. In addition, the order of lookup tables and memory units are also reduced. Under realistic standard driving loads including DDC and NEDC and practical laboratory tests, the proposed technique showed a significant reduction in the processing time in comparison with the existing technique. Hence, we believe the proposed ORC technique is a strong candidate for the real-time battery management applications.

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