Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2017) 25: 2860 – 2870

doi:10.3906/elk-1602-118

A parametric battery state of health estimation method for electric vehicle applications

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Received: 09.02.2016 • **Accepted/Published Online:** 11.11.2016 • **Final Version:** 30.07.2017

Abstract: Lithium-ion batteries are commonly preferred in electric vehicle applications. The relative capacity and state of health of a battery decrease with age. Therefore, accurate estimation of these parameters is essential. In this study a parametrical approach for estimation of battery state of health is proposed. A hybrid battery model that has a maximum error less than 3% is used. The relative capacity of the battery is estimated by using performance decrement with age. The method is validated by two different set of experiments. The first set is conducted with batteries that were aged by a controlled process and the second set is conducted with randomly aged batteries. The proposed method works successfully in both conditions with maximum error less than 5%.

Key words: Lithium-ion batteries, battery management systems, battery state of health, electric vehicles

1. Introduction

Today electric vehicles (EVs) are one of the cleanest alternatives in the transportation field considering environmental factors. Lithium batteries are commonly used in EV applications thanks to their higher open circuit voltages and efficiency, longer cycle life, and lower self-discharge rate when compared with other battery types [1–5]. Accurate information about the remaining battery life is important for reliable operation in EV applications. Therefore, a parameter called battery state of health (SoH) is defined that basically indicates battery health. The value of SoH demonstrates a comparison between the actual and initial conditions of a battery. The unit of SoH is percent points and 100% SoH means the battery has the specifications of a brand new battery. SoH also provides an idea about remaining battery life. Additionally a battery should not be used with SoH below 80% [6].

There is a multiplicity in the definition of SoH in the literature [7]. Moreover, there is a wide spectrum of methods about estimation or determination of SoH. SoH can be determined by using electrochemical impedance spectrometry measurement [8]. However, advanced techniques are needed for measurement of SoH and online measurement is not possible. Therefore, estimation-based methods are more popular. Advanced regression, classification, and state estimation algorithms can be used for collecting data for battery health management [9]. A statistical parametric model is also developed in order to estimate error time [10]. A model was proposed for crank capability prognosis and impedance spectrometry was used [11]. In some studies the focus is directed towards hybrid EVs where state estimation techniques such as the extended Kalman filter are used [12,13]. Autoregressive integrated moving average and artificial neural networks are also used for both clustering of

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measured data and estimation [14]. Dynamical models representing nonlinear potentials of lithium-ion batteries such as temperature changes, heat effects, and transient response are proposed in [15]. These models are developed by resistive companion method to avoid electrochemical calculations. Several battery parameters are estimated using operating current and voltage quantities in an electrical battery model [16]. In order to attain a dynamic estimation, an adaptive observer is designed and Lyapunov stability theorem is used to ensure observer convergence. In [17] pattern recognition is used to monitor the health of batteries in a stack. However, determination or estimation of the remaining battery life is difficult when the environmental conditions and load variations are considered. There are studies in which a support vector machine (SVM) [18] and a Bayesian implementation of generalized linear form of SVM, relevance vector machine employing particle filter algorithms [19], are used. In a more recent study dynamic Bayesian networks are also used [20]. A discrete wavelet transform is also used to extract information about battery health using an electrochemical model [21]. A very detailed review can be found in [22]. The method proposed in the present study is a simple method that requires less computational effort while providing accuracy. Although the method can only be employed in a specific driving cycle, it is obvious that slopes in the driving cycle used in SoH estimation can be adopted for online applications in EVs.

The capacity of a battery can simply be defined as the length of time that a fully charged battery can be totally discharged under nominal discharge current. The maximum capacity of a battery decreases with battery age. The change in capacity can be indicated with a parameter, relative capacity (RC), which is the comparison of maximum capacity of a battery to its initial maximum capacity. The unit of RC is also percent points. The main purpose of the present study is to indicate the SoH of a battery in terms of RC. In order to achieve this goal the reference cycle number of the battery (RCN) is used. RCN is the cycle number of a battery that was aged by using the manufacturer's procedures as mentioned in the technical specifications manual. If the condition of a battery is represented in terms of RCN, RC can also be calculated by this relationship.

Battery performance can be related to several factors such as voltage imbalances in a stack, temperature, or health of a battery. In EVs battery temperatures or balancing issues are mostly controlled by thermal or battery management systems. Therefore, performance degradation can be a measure that indicates battery health, assuming a stable battery temperature and balanced cells in the stack.

In the present study RCN is determined by using the performance degradation of the battery with age. In order to obtain SoH, RC is calculated by using RCN. For this purpose a battery model capable of reflecting the changes in battery parameters during aging is required. Thus a previously proposed battery model [23] was improved and used to simulate the behavior of a battery at different cycles. The battery model has a maximum error less than 3%. RCN is obtained by a parametrical method in which the simulation results are used. The method is validated by experiments in which both batteries aged by a controlled process and randomly aged batteries are used. The proposed method works successfully in both conditions with a maximum error less than 5%. Assuming that an EV should have a successful thermal management system to keep battery temperature around the optimum operating temperature, changes in temperature are not reflected in the battery model. Thus both the battery model and the SoH estimation method are independent of temperature.

2. Battery model

Modelling of a battery is a difficult task because of the complex electrochemical structure and nonlinear characteristics. The criteria needed to design an accurate battery model and to compare it with existing models can be summarized as accuracy, calculation time, number of parameters, contribution required from other disciplines, and analytic structure. Battery reactions must be defined to develop a mathematical relationship between aging and health in batteries. For this purpose, a model capable of reflecting aging effects of the battery is needed. Therefore a previously proposed battery model [23] is improved and used in this study.

In this study Kokam LBP55205130H [24], 11-Ah automotive grade LiNiMnCo4 batteries are used. Within the scope of this work a relationship between battery cycle life and battery terminal voltage is established and adopted to the battery model. The proposed model is able to obtain terminal voltage of the battery, V_t, with respect to open circuit voltage, V_{OC}, which was recorded in no-load condition. The value of V_{OC} is calculated by a mathematical function that represents the correlation between battery capacity and V_{OC}. In the model a parallel RC block in series with a resistor is used to increase accuracy in transient conditions. Although both the accuracy and the complexity of the model increase by enhancing the number of RC blocks, a single RC block produced satisfactory results without sacrificing simulation performance. The model can be seen in Figure 1.

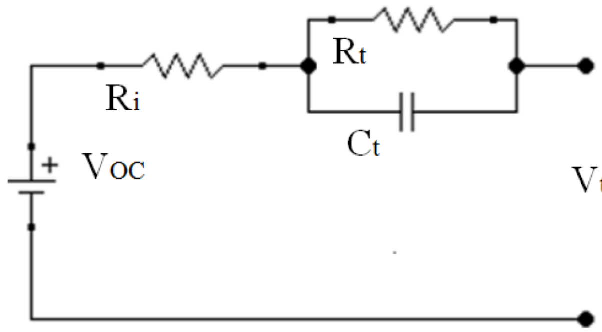

Figure 1. Electrical equivalent circuit battery model.

V_{OC} of a battery can be obtained depending on the value of SoC and SoC can be obtained by using several methods including Coulomb counting. In the proposed model, a set of experiments was performed [23]. By interpreting the experimental results and using mathematical methods V_{OC} is defined as an exponential function of SoC as

$$V_{OC} = -1.035e^{-25\,SoC} + 0.325\,SoC^2 + 0.495\,SoC + 3.575 \tag{1}$$

To study the effects of aging on a battery the model should reflect the capacity changes of the battery at different cycles. For this purpose, V_{OC} is multiplied by an aging coefficient. The value of this coefficient is taken from a look-up table formed using the information given by the manufacturer, which is shown in Figure 2.

2.1. Verification of the model

In order to determine the accuracy of the model a simulation was done in Simulink environment. Constant discharge current of 11 A was applied to the battery model. The V_{OC} values were generated by a mathematical function block that employs Eq. (1) depending on SoC level. Thus terminal voltage V_t can be produced as seen in Figure 3 faithfully representing the terminal voltage curve of an actual battery. As seen from Figure 3, measured and experimental data are in close agreement. The average error is 0.422% while the maximum error is less than 3%.

3. Relative capacity estimation method

The relative capacity of a battery decreases with age and information about this parameter is provided by the manufacturer. For instance, the relative capacity over cycle number curve of the battery that was used in this

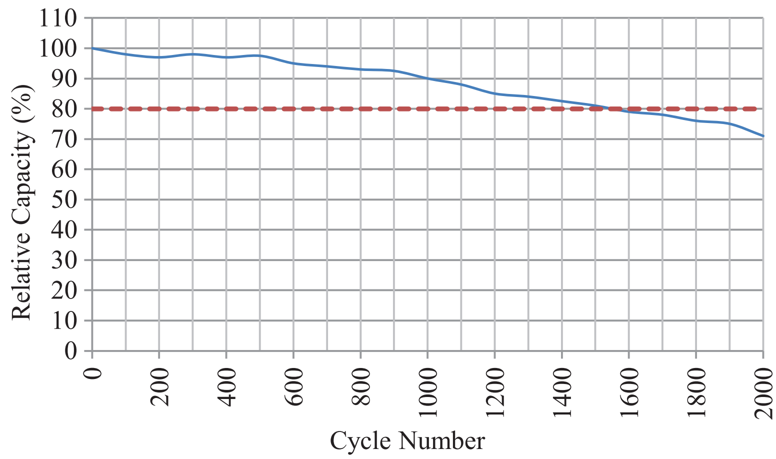

Figure 2. Relative capacity over cycle number graphic for the battery.

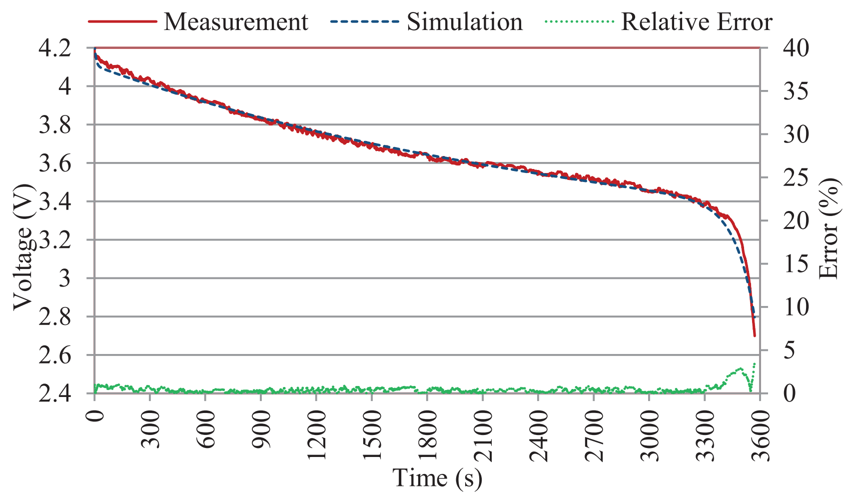

Figure 3. Comparison of simulation and experimental results.

study is given in Figure 2. The blue solid line is the relative capacity of the battery and the red dotted line is the limit of battery capacity for safe and reliable operation [24]. However, manufacturers have standard charge and discharge routines for the aging process. For the battery used in this study a charge/discharge cycle is summarized as below.

The charging sequence is named constant charge/constant discharge (CC/CV) and the first battery is charged with constant 11 A until it reaches 4.2 V; then charging is continued for 5 h or until the battery current falls below 0.055 A. In the discharge sequence the battery is discharged with constant 11 A until battery terminal voltage falls to 3.0 V. There is a rest time of 10 min between charge and discharge sequences and all this process continues at 23 $\pm$ 3 $^\circ$C [24].

It is not possible for an EV battery to be aged ideally in a similar cycle as the manufacturer's aging test above. Thus the aim of the present study was to develop a technique that is able to estimate the RC of any battery.

Batteries give different reactions to same inputs at different ages. In Figure 4 the outputs of the same battery at different ages are given. The input signal that the batteries were subjected to is a test cycle derived from ECE15 Urban Driving Cycle. The blue solid line is the response of the battery at 100 cycles and the red dotted line is the response of the same battery at 700 cycles. As can be seen from the figure, there are especially three zones in which the response of batteries can clearly be separated from each other. In the proposed method the RCN of a battery to which the specified driving cycle is applied will be calculated by using the slopes in zones.

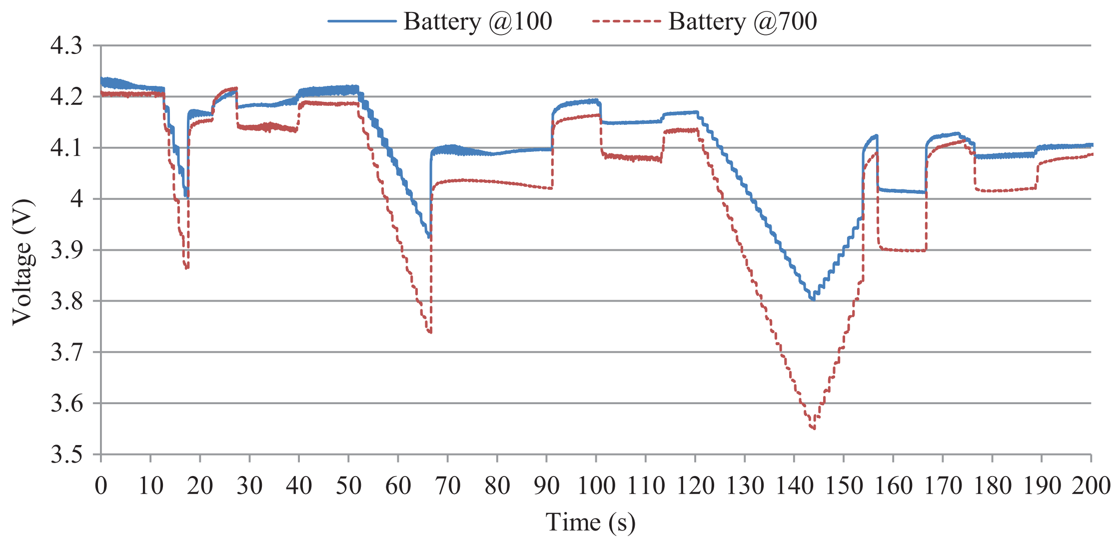

Figure 4. Reaction of two different aged batteries to the same driving cycle.

In the estimation method the parameter " αa" is described and the value of α is extracted from simulation results of the battery model for every 100 cycles. Next, an equation that gives the RCN of a battery is obtained depending on α values. Then an equation to obtain the SoH of a battery depending on RCN is proposed. Thus, with the proposed method the SoH of a battery can be estimated by finding α, which can be obtained by measuring the voltage drop ratio.

3.1. RCN estimation

The slope of the voltage degradation in Figure 4 can be represented by a parameter for comparison of battery responses. A linear voltage signal can be represented as in Eq. (2), where α and b are the parameters, V_t is voltage, and t is the corresponding time values in our problem.

$$V_t = \frac{b}{a+t} \tag{2}$$

The parameters α and b reflect the difference between the slopes of lines. These parameters can be obtained by using two voltage values during the slope.

$$a = \frac{V_2 t_2 - V_1 t_1}{V_1 - V_2},\ b = \frac{V_1 V_2 (t_2 - t_1)}{V_1 - V_2}, \tag{3}$$

where V_1 and V_2 are the voltage values observed at t_1 and t_2 instances, which are the starting and finishing instances of slopes, respectively. Because these two parameters are dependent on each other they will give the same results.

In the test cycle the first, second, and third zones last 1–6, 41–56, and 111–136 s, respectively. Because the test cycle is used in both simulation of the model and validation tests for the method, time values are accepted as $t_1 = 1$, $t_2 = 6$ s for the first zone, $t_1 = 1$, $t_2 = 16$ s for the second zone, and $t_1 = 1$ and $t_2 = 16$ s for the third zone. The simulation results for a battery of every 200 cycles of age for first zone are given as an example in Table 1. In the table given quantities are the recorded voltage values in corresponding seconds of the simulation.

Table 1. Reaction of two different aged batteries to the same driving cycle.

Time (s)	Age (cycle number)					
	1	400	800	1200	1600	2000
1	4.310	4.310	4.310	4.310	4.310	4.310
2	4.294	4.269	4.244	4.207	4.161	4.108
3	4.274	4.221	4.169	4.093	3.999	3.892
4	4.249	4.167	4.086	3.970	3.827	3.663
5	4.219	4.108	3.996	3.838	3.644	3.421
6	4.187	4.045	3.903	3.702	3.457	3.175

For the simulation results in Table 1, a and b can be obtained as given in Table 2, by using Eq. (3).

Table 2. Parameter values for the first zone.

Parameter	Age (cycle number)						
	1	400	800	600	1200	1600	2000
α	169.3	75.4	46.9	58.4	29.4	19.2	13
b	733.9	329.1	234.6	256	131.1	87.3	60.3

The changes in the values of parameters for age are taken into account to generate a function for RCN. By using curve fitting and the parameter values given in Table 2, Eqs. (4) and (5) are generated to calculate the value of RCN depending on parameters a and b, respectively.

$$RCN\,(a_1) = -0.001371a_1^3 + 0.4846a_1^2 - 58.15a_1 + 2579 \tag{4}$$

$$RCN\,(b_1) = -0.001713b_1^3 + 0.02631b_1^2 - 13.71b_1 + 2637, \tag{5}$$

where the subscript represents the zone to which the parameter belongs.

Equations for the other zones were also generated with the same logic and are given in Eqs. (6), (7), (8), and (9).

$$RCN\,(a_2) = -0.0003195a_2^3 + 0.179a_2^2 - 35.28a_2 + 2642 \tag{6}$$

$$RCN\,(b_2) = -4.019 \times 10^{-6}b_2^3 + 0.009731b_2^2 - 8.29b_2 + 2678 \tag{7}$$

$$RCN\,(a_3) = -1.612 \times 10^{-4}a_3^3 + 0.1074a_3^2 - 25.82a_3 + 2233 \tag{8}$$

$$RCN\,(b_3) = -2.055 \times 10^{-6}b_3^3 + 0.005887b_3^2 - 6.09b_3 + 2259 \tag{9}$$

3.2. Battery SoH estimation

In this study SoH is indicated as relative capacity. The SoH of a battery can be estimated by using RCN and the correlation between RCN and capacity, which is given in Figure 2. If the graphic in the figure is smoothed by moving average method, maximum capacity can be represented as an 8th order polynomial in terms of RCN as given in Eq. (10).

$$\begin{aligned} SoH\% \quad = \quad & 1.165 \times 10^{-17} RCN^6 - 8.103 \times 10^{-14} RCN^5 + 2.15 \times 10^{-10} RCN^4 - 2.66x10^{-7} RCN^3 \\ & +1.441 \times 10^{-4} RCN^2 - 0.3418 RCN + 99.95 \end{aligned} \tag{10}$$

4. Test results

Two different tests were carried out for validation of the method: controlled and uncontrolled tests. For controlled tests a battery is aged for 500 cycles with recommended charge/discharge procedures. Consequently cycle age of this battery shows the actual RCN with this method. The RCN determination method is applied to the battery for every 100 cycles. On the other hand, 5 different batteries that were previously employed in different applications are used in uncontrolled tests. Neither are they aged with recommended procedures nor is there any information about their health.

For both tests actual capacity values of test batteries must be compared to estimated SoH value to evaluate the success of the proposed method. Actual capacity may be measured by discharging a fully charged battery with rated current. The capacity of a test battery is 11 Ah. Thus a battery with RC of 100% must be totally discharged in 3600 s with rated current of 11 A. For capacity measurement test batteries are discharged with 11 A current and their discharge time is compared with 3600 s.

4.1. Controlled tests

In these tests a battery is aged for 500 cycles with recommended procedures and the test cycle is applied to the battery every 100 cycles.

In Table 3, experimental results are shown for every 100 cycles of the battery where V_1 and V_2 are the voltage values recorded in t_1 and t_2, which are the starting and finishing instances of slopes, respectively.

Table 3. Experimental data of the battery which was aged with catalogue procedures.

Zone	Cycle number	100	200	300	400	500
1	V_1	4.209	4.214	4.188	4.207	4.201
	V_2	4.048	3.982	3.902	3.871	3.815
	t_1	12.058	10.9	12.4	10.579	13.519
	t_2	17.868	16.858	18.68	16.809	19.505
2	V_1	4.209	4.183	4.168	4.188	4.172
	V_2	3.931	3.845	3.784	3.753	3.698
	t_1	51.337	51.099	52.819	52.578	53.499
	t_2	67.326	67.798	67868	66.99	67.455
3	V_1	4.176	4.146	4.146	4.137	4.13
	V_2	3.698	3.589	3.477	3.405	3.367
	t_1	121.87	121.39	122.51	120.75	120.63
	t_2	146.78	146.09	147.08	145.57	144.77

The value of α may be obtained as in (3) by using gathered voltage and time values. Subsequently RCN may be calculated by using Eqs. (4), (6), and (8) for the first, second, and third zones, respectively. In Table 4 values of α RCN and the difference between RCN and actual cycle number are given for all three zones.

Table 4. Comparison of estimated and calculated cycle numbers in controlled tests.

Zone	Cycle number	100	200	300	400	500
1	Value of parameter αa	148.72	103.72	87.359	72.685	59.852
	Calculated cycle number	139.43	231.15	283.31	386.09	540.61
	Error (%)	39.43	15.57	5.56	3.47	8.12
2	Value of parameter α	230.32	183.02	152.46	127.05	11.649
	Calculated cycle number	108.16	222.19	291.63	393.80	489.68
	Error (%)	8.16	11.10	2.79	1.55	2.06
3	Value of parameter α	197.11	157.84	131.61	119.31	110.27
	Calculated cycle number	75.95	194.64	323.64	403.87	472.29
	Error (%)	24.050	2.68	7.90	0.99	5.52

In Table 5 the comparison between the measured capacity and the estimated SoH is given for all three zones.

Table 5. Comparison of estimated SoH and measured capacity values in controlled tests.

Zone	Cycle number	100	200	300	400	500
1	Estimated SoH (%)	97.342	97.025	97.027	97.047	96.472
	Measured capacity (%)	102.167	100.667	98.167	97.694	97
	Error (%)	4.723	3.617	1.162	0.663	0.535
2	Estimated SoH (%)	97.631	97.033	97.031	97.039	96.774
	Measured capacity (%)	102.167	100.667	98.167	97.694	97
	Error (%)	4.440	3.609	1.157	0.671	0.233
3	Estimated SoH (%)	98.076	97.082	97.049	97.027	96.085
	Measured capacity (%)	102.167	100.667	98.167	97.694	97
	Error (%)	4.004	3.561	1.139	0.683	0.155

4.2. Uncontrolled tests

Uncontrolled tests were undertaken with five different batteries that were previously employed in several applications and tests. Thus these batteries are not aged with standard procedures and their cycle numbers are unknown. In the first phase, experimental results of the batteries under the test driving cycle are used in the proposed method. Then RCN and SoH estimations are performed. In the second phase capacities of tested batteries are measured and compared with estimated values. In Table 6 the experimental results of the 5 different batteries are given for all three zones.

In Table 7 the value of α, the calculated cycle number by using α, and the estimated SoH value for that cycle number and the obtained capacity value are given.

The maximum capacity of battery #3 was very low as can be seen from Tables 7 and 8. The battery was fully emptied during the 3rd slope. Thus there are no available time, voltage, or α values for this battery for the 3rd slope.

5. Conclusions

Accurate estimation of the SoH of a battery has vital importance for battery applications. In this study a novel, analytical approach for SoH estimation of an automotive grade lithium-ion-polymer battery is proposed. The proposed SoH estimation method is based on an accurate battery model and RCN estimation. Although the

Table 6. Experimental results for 5 batteries without aging information.

Zone	Battery ID	#1	#2	#3	#4	#5
1	V_1	4.216	4.216	4.193	4.205	4.186
	V_2	4.054	4.014	3.166	4.005	4.005
	t_1	12.45	12.47	11.939	13.758	12.918
	t_2	17.87	17.218	16.518	20.238	17.781
2	V_1	4.214	4.195	4.136	4.191	4.171
	V_2	3.944	3.815	2.651	3.904	3.828
	t_1	51.937	51.658	82.039	53.778	52.5
	t_2	66.857	66.558	66.349	68.793	68.089
3	V_1	4.17	4.169	N/A	4.162	4.141
	V_2	3.67	3.569	N/A	3.65	3.585
	t_1	122.157	122.257	N/A	124.356	122.739
	t_2	146.28	146.446	N/A	147.404	145.629

Table 7. Comparison of estimated and measured capacity values in uncontrolled tests.

Zone	Battery ID	#1	#2	#3	#4	#5
1	Value of parameter α	137.77	95.375	13.638	132.16	109.91
	Calculated cycle number	180.53	251.61	1872.6	193.30	221.47
	Estimated SoH (%)	97.124	97.018	74.808	97.085	97.034
	Measured capacity (%)	99.722	98.583	77.666	101.33	100.05
	Error (%)	2.605	1.587	3.679	4.192	3.0193
2	Value of parameter α	221.69	152.70	26.126	208.94	178.84
	Calculated cycle number	136.93	290.92	1836.7	170.67	230.01
	Estimated SoH (%)	97.360	97.031	75.452	97.162	97.026
	Measured capacity (%)	99.722	98.583	77.666	101.33	100.05
	Error (%)	2.179	1.574	2.850	4.116	3.027
3	Value of parameter α	180.37	147.35	N/A	168.61	152.31
	Calculated cycle number	114.577	240.10	N/A	155.00	217.69
	Estimated SoH (%)	97.549	97.021	N/A	97.241	97.038
	Measured capacity (%)	99.722	98.583	77.666	101.33	100.05
	Error (%)	2.179	1.584	N/A	4.038	3.015

Table 8. Summary of errors of the controlled tests.

	Zone 1	Zone 2	Zone 3	Average
RCN prediction error (cycles)	28.35	11.02	16.93	18.77
RCN prediction error (%)	14.43	5.13	8.23	9.26
Capacity estimation error (%)	2.14	2.02	1.91	2.02

method can only be employed in a specific driving cycle, it is obvious that slopes in the driving cycle used in SoH estimation can be adopted for online applications in EVs.

The battery model is an electrical equivalent circuit battery model that contains a mathematical function to determine its open circuit voltage when it is loaded. Parameters for the model were extracted using results of a series of experiments. The model is simulated in MATLAB/Simulink environment and the maximum error is less than 3%.

The performance of a lithium-ion-polymer battery decreases over time and different aged batteries have different responses under the same conditions. In this study a parameter-based function was developed to reflect these changes in a battery. The SoH estimation method is combined with an RCN estimation method where this parameter was used. Validation of the method was performed using two different test procedures and the results were compared with maximum usable capacities. Tests were carried out both with batteries aged by aging procedures of the manufacturer and with batteries randomly aged where average errors for SoH estimation are 2.02% and 2.823%, respectively.

6. Acknowledgment

This work was financially supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK), project number 110E209.

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