State-of-Health Estimation for Lithium-Ion Batteries in Real-Time Embedded Applications.

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Abstract— **Determining the lithium-ion batteries' state of health (SOH) is essential to making sure they run securely and last a long time. Due to restrictions in the hardware components, the current methods for estimating SOH on embedded systems only take into account one health indicator (HI) to represent either capacity or internal resistance (IR) behavior. However, neither capacity nor IR could be disregarded as they both offer useful battery health information. We thus provide the SOH estimate approach, which can express it using HIs that can be directly monitored in embedded systems with less complex composition, and can take into account both capacity degradation and IR expansion. The suggested approach, according to the data, decreases the infer-ence time by an average of 29.20% and increases estimation accuracy by at least 47.59%. The suggested method's correctness and efficacy are demonstrated and confirmed through the use of many datasets in an actual embedded system.**

I. INTRODUCTION

Nowadays, lithium-ion batteries are frequently employed as the primary power source in a variety of applications, including home appliances, electronics, and electric cars. [1].It is imperative to properly manage a battery to ensure both safety and longevity.With a battery management system (BMS), this is possible.One of the key functions of a BMS is the state-of-health (SOH) estimation, which provides valuable data to shield the battery from early failure and to increase its durability. [2].Precise SOH estimations can avert malfunctions that may arise from using a low-charge battery continuously.Numerous strategies have been put out to increase the accuracy of the SOH estimation.Certain researchers have employed model-based techniques, such the equivalent circuit model (ECM) and the electrochemical model.[3]–[5].Liuetal.[3] suggested an ECM based on internal resistance (IR) increase for SOH estimate. The simulated model's excellent accuracy is demonstrated by the result [3], however the accuracy of the battery model affects the model's performance.Eddahecharol.[4]calculated SOH utilizing the data in IR growth

. IR is monitored using impedance spectroscopy. Although the model in [4] has high simulation accuracy, it is difficult to simulate impedance spectroscopy in embedded systems since it requires com-plex battery data analysis to represent the behavior of IR. To achieveSOHestimationinembeddedsystems,Verma*etal.*[5] proposed a reduced-order ECM. The model in [5] has been implemented in an embedded system and the performance accuracy increases by 3% compared to the conventionalECM. Nonetheless, the ECM-based model is not able to accu- rately generalize for other types of batteries. That is, theECM-based models need to be redeveloped to characterizethe behavior of other types of batteries.

To cope with the drawbacks of the above approaches, Chemali [6] used data-driven methods instead of using ECM to perform SOH estimation. The result shows that the model cancapturetheuncertaintiesofcapacitydegradationdueto the model's adaptability to nonlinear systems. Although data-driven methods have several advantages, challenges still exist in terms of algorithm design and computation time for embedded system applications. Qu *et al.* [7] utilized a deep learning technique to estimate SOH based on capacity degradation. This process is time consuming and has a high-power demand. Since calculating the battery capacity requires complex integration operations which is not suitable for real-time applications with embedded systems.

Therefore, several researchers have proposed novel health indicators (HIs) as a substitute for battery capacity data to achieveimplementationforreal-timeapplicationswithembedded systems [8], [9]. Shen *et al.* [8] used the voltage, current, andchargingcapacitytoestimateSOH.DespitetheuseofHIs in [8], the algorithm still requires high memory and power of embeddedsystemsduetocomplexintegrationfromthecapacitycalculation.ToreducecomplexityinextractingHI,Chaoui and Ibe-Ekeocha [9] used measurable battery data, such as voltage, charge/discharge currents, and ambient temperature variations as HIs to substitute capacity degradation. Although thesestudiesusedHIstoestimateSOH,theHIsareused to reflect the capacity degradation only which disregards the influence of IR growth. On the other hand, IR growth and capacitydegradationareequallyimportantfactorsforaccurate SOHestimation [10].Particularly,capacitydegradationrepresents battery aging which indicating when a battery should be replaced and IR growth provides the failure indication, thus neither of these could be neglected. Hence, we propose the SOH estimation method that considers both capacity degradation and IR growth by representing it with HIs that can be directly measured in an embedded system with less complex computation.

Thecontributionsofthisletterareasfollows.

1) We utilized HIs that can be extracted without complex computation which enables real-time SOH estimation.

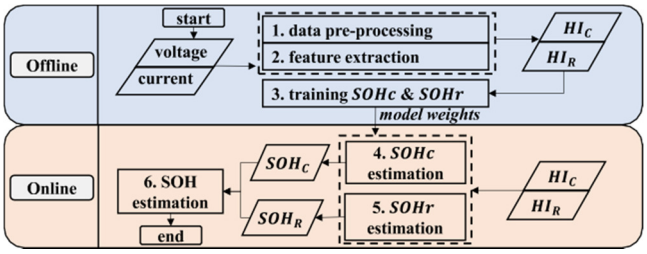

Fig.1.FlowchartoftheproposedSOHestimation.

TABLEI
SPECIFICATIONOFBATTERIESDATASETSANDTHECORRELATION COEFFICIENTSBETWEENHISANDIR/CAPACITY

Datasets	Initial Capacity (Ah)	Cut-off Voltages (V)	The Correlation Coefficients	
			HI_R reflecting IR growth	HI_C reflecting capacity degradation
BEXEL cell #7	7.08	2.5, 4.2	0.956	0.948
BEXEL cell #13	7.14	2.5, 4.2	0.982	0.943
NASA cell #6	2.04	2.5, 4.2	0.921	0.870
NASA cell #7	1.89	2.2, 4.2	0.948	0.889

2) To improve the SOH estimation accuracy, we utilized the relationship between capacity degradation and IR growth.

II. SOHESTIMATIONMODEL

The proposed SOH estimation is illustrated in Fig. 1. We utilized HIs that are directly measurable using embedded systemsapplications.TheHIsarefedtoarecurrentneu- ral network (RNN) that estimates both 1) SOH based on capacity degradation *(SOHc)*; and 2) SOH based on an IR growth(*SOHr)*.ToimprovetheSOHestimationaccuracy,the relationship between *SOHc* and *SOHr* was analyzed.

A. ExtractionofHealthIndicators

WeextractedHIsfromtwodifferentbatterydatasets: 1) NASA[11]and2)BEXEL[12].BothNASAand BEXEL datasets are extracted from lithium-ion batteries. These datasets consist of the measured voltage, current, temperature,capacity,andIR.Measurementsareperformedduring charging under constant current constant voltage (CC+CV) profile and during constant current discharging. The charge–discharge profile of two battery datasets is listed in Table I. Specifically, the NASA dataset provides information of four cells: 1) cell#5; 2) cell#6; 3) cell#7; and 4) cell#18, whereas the BEXEL dataset provides the same for two cells: a) cell#7; andb)cell#13.ThesenumbersarecellIDsassignedbyNASA and BEXEL to identify the cells.

ThemeasuredcapacityandIRdataarerequiredforestimat- ing the SOH, but the NASA dataset only provides IR data of cell#6andcell#7.Therefore,weonlyusedthesecellsfromthe NASA dataset. In the HIs extraction process, we divided the HIs into two categories: 1) HIs that reflect the capacity degradation; and 2) those that reflect the IR growth. To analyze the correlation between these HIs and the corresponding output, we used the Person correlation coefficient which is defined as

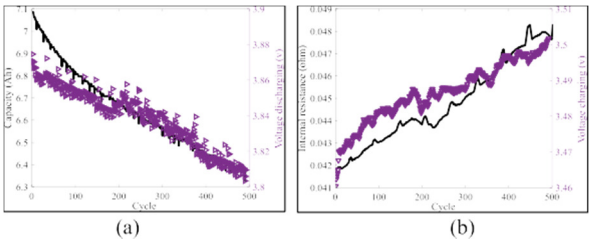

Fig.2. (a)HIsreflectingthecapacitydegradation.(b)HIsreflectinganincrease in IR.

follows[13]:

$$\rho(A,B)=\frac{1}{N-1}\sum_{i=1}^{N}\frac{A_i-\mu_A}{\sigma_A}\frac{B_i-\mu_B}{\sigma_B} \quad (1)$$

where N is the number of observations, A is HIs, B is capacity or IR, $\mu_A$and $\mu_B$are the mean values of A and B, and $\sigma_A$and $\sigma_B$are the standard deviation of A and B.

*1) HIs Reflecting Capacity Degradation:*In terms of SOH estimation, capacity degradation is the main factor because it indicatesthedegradationofbatteryhealth.Toreducethecom- putational complexity, capacity degradation is replaced with thefirstvoltagevalueinthedischargingprocess.Therelation- ship between the charging–discharging cycle with the: 1) first voltage value in the discharging process (HI_C); and 2) capacity degradation is shown in Fig. 2(a). As shown in the figure, both the capacity and HI_Cdegrade with an increasing num-ber of cycles. In addition to that, the correlation coefficients betweenHI_CandcapacitydegradationarepresentedinTableI. ItshowsthecorrelationcoefficientsbetweenHI_Candcapacity degradation are greater than 0.8 using the NASA dataset and even greater than 0.9 for the BEXEL dataset. Therefore, $HI_C$was found to be capable of reflecting the capacity degradation. Accordingly, $HI_C$is used to estimate the SOH based on capacity.

*2) HIs Reflecting Increase in Internal Resistance:*The IR growth in a battery is also used as an indicator of battery health. To reduce the computational complexity, we replaced theIRwiththevaluethatcorrespondstothefirstvoltagevalue during the charging process (HI_R). The $HI_R$and the IR versus cycleareshowninFig.2(b).Asshowninthefigure,both IR and voltage increase with the number of cycles. That is,$HI_R$of the first and last cycles is 3.462 and 3.478 V, respectively,andtheIRvalueofthefirstandlastcyclesis0.0418 ▲ and 0.0478 value of the first and last cycles, respectively. In additiontothat,itscorrelationcoefficientisgreaterthan0.9for all datasets as shown in Table I. Therefore, $HI_R$was found to be capable of reflecting the IR increase. Accordingly, we used it to estimate SOH based on resistance.

B. SOHEstimationFramework

In existing approaches, the training process of SOH estimation is based on a single type of HI that either reflects capacity degradation or IR growth. However, capacity degradation and IRgrowth exhibit different behaviors, which might havedifferenteffectsonthebatterySOH.Therefore, itisonly reasonable to consider both factors. Accordingly, we proposea battery health estimation method considering both capac-ity and IR. The overall proposed SOH estimation frameworkis illustrated in Fig. 1. This framework starts with the collectionoftherawvoltageandcurrentdata.Preprocessing

techniques were used before initializing the feature extraction process; these include: 1) data cleansing; and 2) normalization. Data cleansing is the process of removing outliers in the datatopreventunderfittingandnormalizationistheprocessof scaling the data to values between 0 and 1. These techniques were performed offline and only in the training process. We computedatapreprocessingduringtraining.Then,precompute data preprocessing parameters are used during inference.

After data preprocessing, the features of the HIs were extracted.Then,theHIswerefedtotheRNNtoestimate the SOH. Specifically, a long short-term memory (LSTM)was employed to estimate *SOHc* and *SOHr*. Moreover, we specifiedtheLSTMlayerwith50hiddenunits,followedby a fully connected layer of size 300 and a dropout probabilityof 0.5. The training epochs are set as 500 with mini-batchesofsize50.Weusethemean-squarederrorasalossfunc- tion and the Adam optimizer as the optimization algorithm. These LSTM parameters are carefully tuned and determined by using cross-validation on the training data. Furthermore, in obtaining the SOH estimation model, data obtained from one battery cell (e.g., BEXEL cell #7: 492 measurement data) is used as a training set, and data obtained from another battery cell dataset (e.g., BEXEL cell #13: 438 measurement data) is used as a test set. This process was performed four times to have four test results.

In this letter, *SOHc* is defined as the ratio of the initial battery capacity and its rated capacity [14]. Accordingly, *SOHc*is 100% for a new battery (battery capacity is equal to the nominal capacity) and 0% when the capacity degrades to 80% of the nominal capacity. *SOHc* is expressed as follows:

$$\mathrm{SOH}_c = \left(1 - \frac{C_{\mathrm{int}} - C_k}{0.2 \times C_{\mathrm{int}}}\right) \times 100\% \tag{2}$$

where C_{int} is the initial value of the battery capacity, and $C_k$is thecapacityatthecurrentcycle*k*.Ontheotherhand,*SOHr* is defined as the ratio of the increase in battery IR and the initial IR [14]. It is expressed as follows:

$$\mathrm{SOH}_r = 1 - \frac{IR_{EOL} - IR_k}{IR_k - IR_{\mathrm{int}}} \times 100\% \tag{3}$$

whereIR_kistheIRatthecurrentcycle*k*,$\mathrm{IR}_{\mathrm{int}}$istheIRof a new battery, and $\mathrm{IR}_{EOL}$is the IR value at the end of life where the presumed end of life threshold is 1.33 times of the nominal IR [10].

We estimated the SOH based on both *SOHc* and *SOHr*. Specifically,wetreatedtheestimatedSOHasavariable with two components: 1) *SOHc*; and 2) *SOHr*. We hypoth- esized that both *SOHc* and *SOHr* have a significant effect on SOH.Therefore,neitherofthesecouldbeneglected.Tomodel the relationship between actual SOH, *SOHc,* and *SOHr*, we usedthenonlinearleast-squaremethodintheMATLABcurve-fittingtool.TheactualSOHismodeledusingasecond-degree polynomial surface function *f(X,Y)*, which is expressed as follows:

$$f(X,Y) = c_1 + c_2X + c_3Y - c_4X^2 - c_5Y^2 + c_6XY \tag{4}$$

where X is SOH_c,Y is $\mathrm{SOH}_r$and c_n, $n = 1,\ldots,6$, are the coefficients of the model.

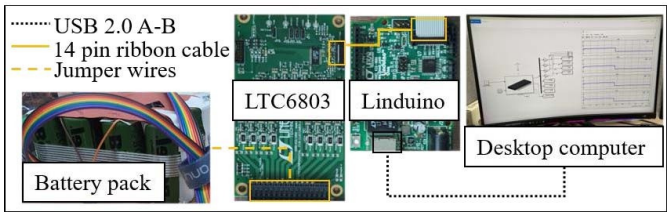

Fig.3.Configurationoftheexperimentalplatform.

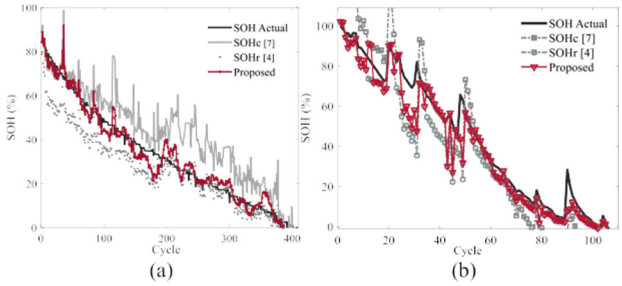

Fig.4.SOHestimationresulton:(a)BEXELcell#7and(b)NASAcell#6.

III. ResultsandDiscussion

A. ExperimentalSetup

The operation of the presented SOH estimation is evaluated using a proof-of-concept experimental setup. The experimental setup is shown in Fig. 3. It includes a BMS board with LTC6803[15],LinduinoUnomicrocontrollerboard [15], acomputer,andtheBEXELbatterypack [12].TheBMS LTC6803boardisusedtomeasurethefirstvoltagevaluein the charging and discharging process as $\mathrm{HI}_R$and HI_C, respectively. Then, the Linduino Uno microcontroller transfers the HI_CandHI_Rtoacomputer.AcomputerwiththeInteli5-6600 CPU 3.30 GHz is used to implement the real-time SOH estimation.Specifically,wecreateafunctiononSimulinkthat contains model weights and bias from trained LSTM. Then, we performed two scenarios: 1) the SOH estimation considering only capacity degradation or only IR growth; and 2) the SOH estimation considering both capacity degradation and IR growth.

B. ResultofSOHConsideringCapacityorIROnly

A single type of HI is represented as *SOHc* and *SOHr*. The estimated*SOHc*and*SOHr*wereobtainedbasedoncapac- ity degradation and IR increase, respectively. As shown inFig. 4(a),*SOHc* can reflect the SOH from the 1st to the 200th charge cycle. After 200 cycles, the estimated *SOHc* differed considerably from that of the actual SOH. On the other hand, the estimated *SOHr* was considerably similar to that of the actual SOH. The gap between the estimated and the actual values of SOH indicates the different effects of capacity and IR on the actual SOH. This result shows that the SOH estimation method based on considering only either the capacity degradation or the IR growth is ineffective in reflecting the actual SOH.

C. ResultofSOHConsideringCapacityandIR

The proposed SOH estimation method considers both the estimated *SOHc* and *SOHr*. As depicted in Fig. 5(a), the estimated*SOHc*and*SOHr*exhibitadirectrelationshipwith

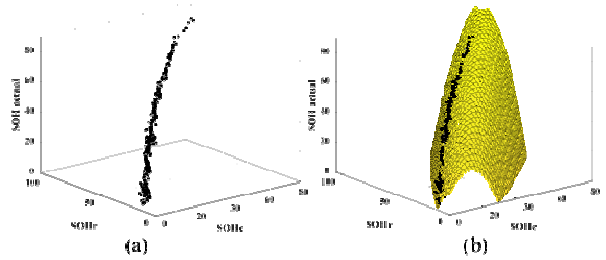

Fig.5. SOHestimationresultonBEXELcell#7:(a)directrelationshipbetween actual SOH, SOH_r, SOH_c; and (b) curve-fitting result.

TABLEII
ERRORSINRMSEATDIFFERENTDATASETS

Datasets	[4]	[7]	**Proposed**	Proposed method improvement over [4] and [7] (%)	
				[4]	[7]
BEXEL cell #7	0.123	0.092	**0.041**	66.26	55.07
BEXEL cell #13	0.192	0.064	**0.033**	82.43	47.59
NASA cell #6	0.102	0.154	**0.036**	64.91	76.57
NASA cell #7	0.112	0.080	**0.028**	74.30	64.04

TABLEIII
COMPARISONOFTRAININGANDINFERENCETIME

	[4]	[7]	**Proposed**
Avg. training time (s)	31	32	**46**
Avg. inference time (ms)	**39.5**	42.7	**30.6**

theactualSOH.Theresultofthebest-fitcurveisplotted inFig.5(b).Thisbest-fitSOHmodelwasapproximatedas a polynomial model, which is expressed as (4). The results in Fig. 4(a) and (b) reveal that SOH estimation is more accurate whenbothcapacitydegradationandIRgrowthareconsidered.
Table II lists the estimation error obtained using our proposed method, [4], and [7]. In estimating the SOH, [4] considersonly IR growth while [7] considers only capacity degrada- tion. The estimation error is defined as the root-mean-square error (RMSE) between the actual SOH and the estimatedSOH. Moreover, we specify the ranges of actual and predictedSOHisfrom0to1.Hence,RMSEof0.041and 0.092 of the SOH estimations represents 4.1% and 9.2% estimation errors, respectively. Aside from the RMSE, Table II also lists the improvement in the accuracy of SOH estima-tion using the proposed method over [4] and [7]. Table II showsthattheaccuracyofSOHestimationusingtheproposed method has improved by up to 82.43% and 76.57% with BEXEL and NASA datasets, respectively. It reveals that the proposedmodelachievessubstantiallybetterperformancethan the other models based on single-type HIs.

We also present the comparison of training and inference time which are shown in Table III. Simulink execution time blockwhichsubtractingthetimestampsforinputandout- put signals is used to obtain inference time. In training, the extraction of HIs is not considered. While during inference,the extraction of HIs must be considered for real-time SOH estimation. Although the proposed method has the longest trainingtime,thisisnottheadditionofthetrainingtimeforthe benchmarking method. This is because we train the proposed multiplesimulationsofamodelinparallel.Ontheotherhand, theinferencetimeoftheproposedmethodwasreducedby an average of 29.20% even though more parameters are considered since the HIs are measurable. Moreover, the result reveals that the proposed method not only improved estimation accuracy but also reduced the computational complexity in real-time SOH estimation.

IV. CONCLUSION

In light of the clear correlation between the SOH predicted using capacity degradation and IR expansion, this letter suggests a real-time SOH estimation approach for embedded applications
1) Reducing the computational complexity in real-time SOH estimation while taking into account the battery health

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