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On-board Capacity Estimation of Lithium-ion Batteries Based on Charge Phase

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Abstract – Capacity estimation is indispensable to ensure the safety and reliability of lithium-ion batteries in electric vehicles (EVs). Therefore it's quite necessary to develop an effective on-board capacity estimation technique. Based on experiment, it's found constant current charge time (CCCT) and the capacity have a strong linear correlation when the capacity is more than 80% of its rated value, during which the battery is considered healthy. Thus this paper employs CCCT as the health indicator for on-board capacity estimation by means of relevance vector machine (RVM). As the ambient temperature (AT) dramatically influences the capacity fading, it is added to RVM input to improve the estimation accuracy. The estimations are compared with that via back-propagation neural network (BPNN). The experiments demonstrate that CCCT with AT is highly qualified for on-board capacity estimation of lithium-ion batteries via RVM as the results are more precise and reliable than that calculated by BPNN.

Keywords: Lithium-ion battery, On-board, Capacity estimation, RVM

1. Introduction

Fossil fuel-based transportation contributes remarkably to global greenhouse gas (GHG) emissions and urban air pollution [1]. Hence electric vehicles (EVs) is widely considered as a promising alternative to reduce the dependence on fossil fuels, cut down GHG emissions, and improve air quality [2]. Therefore, EV technology has developed rapidly in recent years. Nevertheless, there still exist great uncertainties limiting the further market acceptance. One of the most significant factors is the capacity fading of lithium-ion batteries, which can cause an increasingly shorter driving range, thus fairly worrying the drivers during their driving. In addition, severe capacity fading may cause operational disability and even catastrophic failure of the whole system. It's noted that capacity is the amount of electric charge a battery can deliver after being fully charged at its current state. Therefore, it's quite necessary to develop an effective monitoring technique which can accurately estimate on-board capacity to ensure lithium-ion batteries' reliable operation and expand the EVs market acceptance.

In recent years, extensive research work has been conducted on capacity estimation of lithium-ion batteries. The techniques for capacity estimation can be generally divided into three categories: model-based estimation, data-driven estimation and direct measurement, as shown in Fig. 1.

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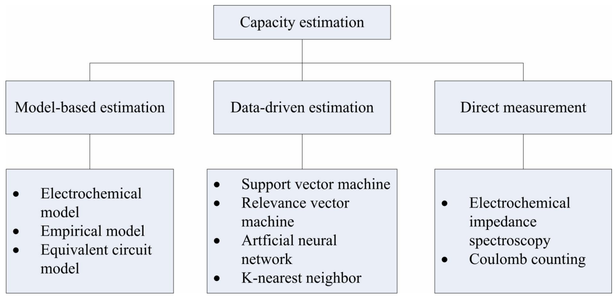

Fig. 1. Techniques for capacity estimation of lithium-ion batteries

Electrochemical model contains some parameters reflecting the battery's health condition in the aspect of electrochemistry, such as cathodic effective porosity and effective conductivity [3]. Once knowing the exact values of these parameters, the capacity can be calculated. The advantage of electrochemical model method is that it provides researchers with insights into what is happening inside the battery. However, it needs much knowledge about electrochemistry, and the model is quite complex to construct.

Empirical model tends to use cycle number to calculate capacity. For example, Micea et al. [4] and He et al. [5] used cycle number to construct a second-order polynomial regression model and exponential model to estimate the capacity, respectively. Yang et al. [6] constructed a two-term logarithmic model to capture the battery degradation trends.

Equivalent circuit model (ECM) [7-16] is the most popular technique in model-based methods. Voltage, current and resistance always exist in the model. Based on some filter methods such as Kalman filter, extended Kalman filter (EKF) and particle filter (PF), some parameters can be obtained to calculate the capacity, e.g., resistance. Though the estimation results are superior to the empirical model, ECM method needs to update the model parameters continually, causing the computation more complex and time-consuming.

Direct measurement obtains the capacity directly from some monitored variants. Coulomb counting method [17] integrates the discharge current over time to obtain the capacity. Though it is easy to conduct, it is not applicable for on-board situation as the EV batteries are seldom fully discharged. Electrochemical impedance spectroscopy (EIS) detects the internal parameters of the battery to calculate the capacity based on the high degree of linear correlation between the capacity and the internal impedance parameter [18]. Nevertheless, EIS is fairly time-consuming and needs special instruments.

As for data-driven method [19-32], capacity is obtained based on a numerical relationship between it and some measured or derived variants. Discharge current, battery power and ambient temperature were used by artificial neural networks (ANNs) to estimate the capacity [33]. Lin et al. [21] employed probabilistic neural network (PNN) which used constant current time, instantaneous voltage drop at the start of discharge and open circuit voltage of a fully discharged battery after resting for one minute as input vectors to calculate capacity. In [23], current-voltage pairs were used to generate symbol strings to construct a special class of probabilistic finite state automata (PFSA) which is then used to acquire a pertinent feature to calculate the capacity. Widodo et al. [24] proposed an intelligent capacity estimation method by means of RVM and SVM with input of discharge voltage sample entropy. Laplacian Eigenmap was used in [34] to estimate capacity. Ambient temperature, charge current, discharge current, discharge cut-off voltage and end-of-life criteria were used to construct the relation between themselves and the capacity. Wang et al. [25] and Weng et al. [26] found the last peak of incremental voltage and incremental capacity have a high linear correlation with capacity, respectively, indicating incremental voltage and capacity can be used to estimate capacity. Zhang et al. [27] used adaptive multi-kernel RVM to estimate on-board capacity based on six novel features extracted from charge and discharge period. Li et al. [35] considered the influence of temperature on the discharge capacity and therefore they constructed a model containing charge capacity, sample entropy of charge temperature and rest time to describe the capacity fading. Liu et al. [29] found the time interval corresponding to a certain discharge voltage difference has a high linear correlation with the capacity, from which the capacity can be acquired. They also found the series of discharge voltage difference of equal time interval has a highly linear correlation with the capacity [22]. Compared with model-based and direct measurement method, data-driven method is much simpler and more accurate.

EVs on the road have a complex condition which is much complex than that in laboratory, causing discharge current and voltage to fluctuate seriously. Therefore, the applicability of above data-driven method based on the discharge phase is questionable for on-board usage. Consequently, more attention should be concentrated on the steady charge phase for on-board capacity estimation with the application of data-driven method.

Best to our knowledge, as for the data-driven method, there are merely two papers only utilizing the charge phase to calculate the capacity. Eddahech et al. [36] used exponential function to fit the current curves in constant voltage (CV) charge phase. They found the exponent in the fitted function has a strong linear correlation with capacity loss, by which the capacity can be calculated. In real applications, every CV charge phase should be fitted in a function, causing it very complex. Furthermore, in order to obtain a satisfying fitting precision, expensive instrument is indispensable to measure the weak current in the trickle charge phase. Hu et al. [37] employed sparse Bayesian learning to investigate the relationship between five variants (i.e., initial charge voltage, the constant current (CC) charge capacity, the CV charge capacity, the final charge voltage and the final charge current) and capacity. Though five variants may improve estimation accuracy, they hugely complicate the computation process. Therefore, it's necessary to propose a method which just needs the data from the battery management system (BMS) to estimate capacity. In addition, considering the BMS' computing ability, the potential method should have a simple calculation process.

Based on experiment, it's found constant current charge time (CCCT) and capacity have a strong linear correlation when the capacity is more than 80% of its rated value, after which the battery should be replaced. Thus this paper employs CCCT to estimate capacity. As demonstrated in [38, 39], ambient temperature (AT) has a significant effect on battery capacity. Hence, it's reasonable to add AT for capacity estimation without causing much more calculation complexity. Relevance vector machine (RVM) is a machine learning technique with successful applications in model regression through nonlinear kernel functions and a number of identified relevance vectors [40]. The RVM owns excellent performance, such as high learning ability, easy training process, and prediction result with probability distribution, through kernel and statistical probability learning [41]. Besides, it has an outstanding computing accuracy and cuts down the computing burden significantly. Hence, RVM is gaining more and more attention in regression. Therefore, RVM is employed with the input of CCCT and AT for on-board capacity estimation of lithium-ion batteries. In order to demonstrate its superiority, it is compared with the back-propagation neural network (BPNN) on estimation results.

The rest sections of this paper are organized in the following order: The RVM algorithm is introduced in

Section 2. Section 3 illustrates the feature extraction in the charge phase. Then, Section 4 makes capacity estimation and compares results between different methods. Finally, some conclusions are given in Section 5.

2. Relevance Vector Machine

2.1 Regression

Given a data set $\{\mathbf{x}_i, t_i\}_{i=1}^{N}, \left(\mathbf{x}_i \in R^d \text{ and } t_i \in R\right)$, the regression relationship between the target and input is formulated:

$$\mathbf{t} = y(\mathbf{x}) + \boldsymbol{\varepsilon} = \boldsymbol{\Phi}\mathbf{w} + \boldsymbol{\varepsilon} \tag{1}$$

where y(·) is a non-linear function; $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_N)^T$ is independent noise with $\varepsilon_i \in N(0, \sigma^2)$; $\mathbf{t} = (t_1, t_2, \ldots, t_N)^T$; $\boldsymbol{\Phi} = (\phi(x_1), \phi(x_2), \ldots \phi(x_N))^T$ is a $N \times (N+1)$ matrix where $\phi(x_i) = \left[1, K(x_i, x_1), K(x_i, x_2), \ldots K(x_i, x_N)\right]^T$; $K(x, x_i)$ is the kernel function; $\mathbf{w} = (w_0, w_1, \ldots, w_N)^T$ is the weight vector.

As t_i is independent of each other, the likelihood for target vector t is:

$$p(\mathbf{t} \mid \mathbf{w}, \sigma^2) = (2\pi\sigma^2)^{-N/2} \exp\left\{-\frac{\|\mathbf{t} - \boldsymbol{\Phi}\mathbf{w}\|^2}{2\sigma^2}\right\} \tag{2}$$

To avoid severe over-fitting which is likely to appear during the process of maximum-likelihood estimation of σ^2 and α, an explicit prior probability distribution over **w** is defined:

$$p(\mathbf{w} \mid \boldsymbol{\alpha}) = \prod_{i=0}^{N} N(w_i \mid 0, a_i^{-1}) \tag{3}$$

with hyperparameter $\boldsymbol{\alpha} = \{\alpha_0, \alpha_1, .., \alpha_N\}$.

Given $\boldsymbol{\alpha}$, the posterior distribution over the weights is:

$$\begin{aligned} p(\mathbf{w} \mid \mathbf{t}, \boldsymbol{\alpha}, \sigma^2) &= p(\mathbf{t} \mid \mathbf{w}, \sigma^2)\, p(\mathbf{w} \mid \boldsymbol{\alpha}) \big/ p(\mathbf{t} \mid \boldsymbol{\alpha}, \sigma^2) \\ &= 2\pi^{-(N+1)/2} |\boldsymbol{\Sigma}|^{-1/2} \exp\left\{-\frac{1}{2}(\mathbf{w} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{w} - \boldsymbol{\mu})\right\} \end{aligned} \tag{4}$$

where the posterior covariance and mean of are respectively:

$$\boldsymbol{\Sigma} = \left(\sigma^{-2}\boldsymbol{\Phi}^T\boldsymbol{\Phi} + \mathbf{A}\right)^{-1} \tag{5}$$

$$\mu = \sigma^{-2}\boldsymbol{\Sigma}\boldsymbol{\Phi}^T\mathbf{t} \tag{6}$$

where $\mathbf{A} = \operatorname{diag}(\alpha_0, \alpha_1, \ldots, \alpha_N)$.

In order to obtain the most-probable point estimate $\boldsymbol{\alpha}_{MP}$, the RVM 'learning' is to maximize the marginal likelihood with respect to α through a type-II maximum likelihood procedure [42]. Many elements of the vector become infinity after marginal likelihood maximization algorithm which is detailedly introduced in [42]. Consequently, the corresponding elements in posterior **w** are extremely concentrated to zero, causing some useless basis functions to be pruned from the matrix $\boldsymbol{\Phi}$ at last. As a result, those training samples that correspond to the non-zero weights become relevance vectors.

2.2 Estimation

After obtaining posterior distribution over **w** based on maximum-likelihood estimation of σ^2 an $\boldsymbol{\alpha}$, *i.e.*, σ_{MP}^2 and $\boldsymbol{\alpha}_{MP}$, the target *t** corresponding to a new test point *x** can be estimated through the distribution:

$$p(t^* \mid \mathbf{t}, \boldsymbol{\alpha}_{MP}, \sigma^2{}_{MP}) = \int p(t^* \mid \mathbf{w}, \sigma_{MP}^2)\, p(\mathbf{w} \mid \mathbf{t}, \boldsymbol{\alpha}_{MP}, \sigma_{MP}^2)\, d\mathbf{w} \tag{7}$$

As both terms in the integrand are Gaussian, we can get: $p(t^* \mid \mathbf{t}, \boldsymbol{\alpha}_{MP}, \sigma_{MP}^2) = N(t^* \mid y^*, \sigma^{2*})$ with:

$$\begin{aligned} y^* &= \mu^T \phi(x^*) \\ \sigma^{2*} &= \sigma_{MP}^2 + \phi(x^*)^T \boldsymbol{\Sigma} \phi(x^*) \end{aligned} \tag{8}$$

*y** is the estimation of *t** and the estimation confidence is determined by variance σ^{2*}, which contains two variance components: the estimated noise on the data and that due to uncertainty in the calculation of the weights.

3. Feature Extraction

The dataset used in our work is obtained from data repository of the NASA Ames Prognostics Center of Excellence (PCoE) [43]. 18650-size lithium-ion batteries composed of $LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$ were run through three different operational profiles: charge, discharge and impedance, described as follows:

Charge step: charging was conducted at a CC level of 1.5 A until the charge voltage reached 4.2 V. Charging was continued in CV mode until the charge current dropped to 20 mA.

Discharge step: discharging was conducted in CC mode until the discharge voltage reached a predefined cutoff voltage.

Impedance measurement: measurement was performed through an electrochemical impedance spectroscopy frequency sweep from 0.1 Hz to 5 kHz.

Repeated charge and discharge cycles resulted in accelerated aging of the batteries. The operation conditions are described detailedly in table 1. It's noted that batteries

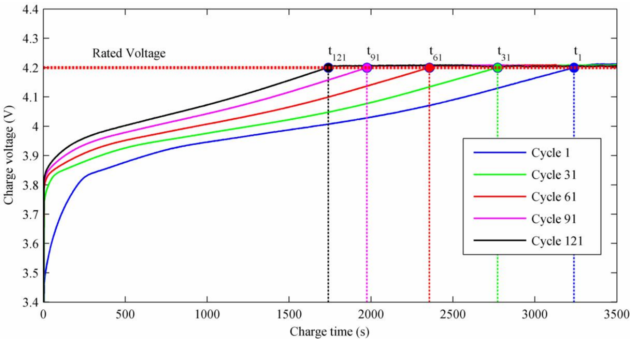

Fig. 2. Decreasing of constant current charge time with the increasing of cycles

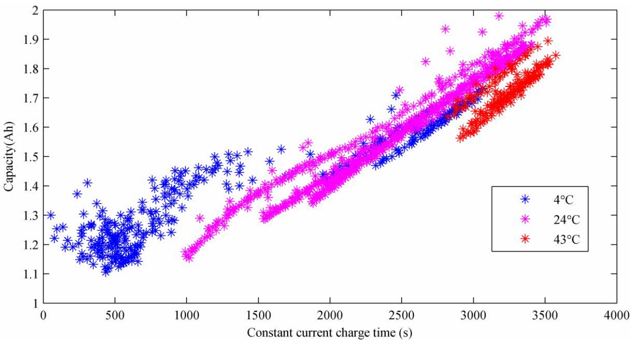

Fig. 3. Influence of temperature on constant current charge time

42, 43 and 44 were sometimes discharged at 2 A or 4 A.

It is quite interesting to find that the CCCT decreases with the usage of battery as shown in Fig. 2. However, the CCCT has different decrease trends at different temperatures as shown in Fig. 3, which illustrates that whatever the temperature is, the CCCT and the capacity have a highly linear relationship as long as the capacity is more than 1.6 Ah (80% of the rated capacity). It can also be observed that at different ambient temperature (AT), the same capacity corresponds to different constant current charge time. Therefore, CCCT is considered as an important feature with addition of AT to estimate capacity for lithium-ion batteries.

4. Capacity Estimation

Thirteen batteries in Table 1 provide offline data for RVM training to construct estimation model, and then the remaining one provides on-board data to validate the robustness and accuracy of the estimation model. This process is called training and validation (T-V). Battery 18, 32 and 47 are used as the remaining one to conduct T-V three times, respectively.

4.1 Evaluation criterion

Three evaluation criteria are chosen to evaluate the

Table 1. Operation conditions of 14 batteries

Battery number	Temperature (℃)	Cutoff voltage (V)	Discharge current (A)
42,43,44	4	2.2, 2.5, 2.7	2 and 4
46,47,48	4	2.2, 2.5, 2.7	1
5,6,7,18	24	2.7, 2.5, 2.2, 2.5	2
29,30,31,32	43	2.0, 2.2, 2.5, 2.7	4

performance and accuracy of the proposed method.

(1) Root mean square error (RMSE)

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(C_i - \hat{C}_i\right)^2}{n}} \tag{9}$$

(2) The fitness degree R^2

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(C_i - \hat{C}_i\right)^2}{\sum_{i=1}^{n}\left(C_i - \bar{C}_i\right)^2} \tag{10}$$

(3) Mean absolute error (MAE)

$$\text{MAE} = \frac{\sum_{i=1}^{n}\left|C_i - \hat{C}_i\right|}{n} \tag{11}$$

where C is the actual capacity, $\hat{C}$ is the estimated capacity, and $\bar{C}$ is mean value of the C, n is the number of the on-board data used for validation.

RMSE is a good measure of local accuracy, used to compare the estimation errors of the model. The smaller the RMSE is, the better the estimation is. The fitness degree R^2 indicates the fitness of data in a statistical model and gives information about the goodness of fitting of a model. The closer R^2 is to 1, the more accurate the estimation is. MAE is used to quantify the error and smaller MAE means better estimation.

4.2 Estimation and discussion

CCCT and AT are input into RVM to estimate capacity. Before T-V, the outliers in the data are deleted and all the input and output data are normalized to range [0, 1].

It's necessary to mention that the kernel function used in this paper is Gaussian kernel function as shown:

$$K\left(x, x_i\right) = \exp\left[-\frac{(x - x_i)^2}{2\gamma^2}\right] \tag{12}$$

where γ is the kernel width.

One of the most prominent contributions in this paper is that the AT is taken into consideration to estimate capacity. In order to demonstrate the effectiveness of our proposed method, the estimation result is compared with that only

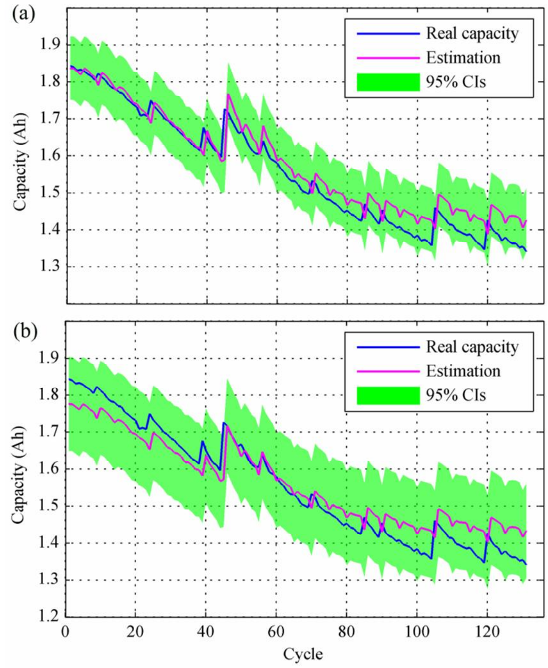

Fig. 4. Capacity estimation of battery 18 (a) considering ambient temperature; and (b) not considering ambient temperature

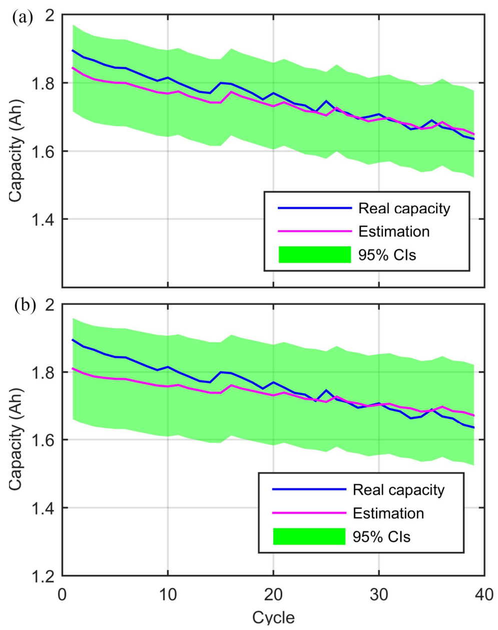

Fig. 5. Capacity estimation of battery 32 (a) considering ambient temperature; and (b) not considering ambient temperature

considering CCCT. The results of estimation and comparison are shown in Fig. 4-6 and table 2.

Fig. 4(b), Fig. 5(b) and Fig. 6(b) show that all the real capacity and the estimations made by RVM considering CCCT share the same attenuation trend. The mean absolute error and average R^2 for the three estimations is 4.73% and 0.9982, respectively. This implies the CCCT can really be used as the feature to calculate the on-board capacity.

Table 2. Capacity estimation results for 3 batteries with or not considering temperature

Battery number	Considering temperature?	R^2	RMSE	MAE
18	Yes	0.9993	0.0426	0.0349
	No	0.9990	0.0485	0.0415
32	Yes	0.9997	0.0294	0.0242
	No	0.9994	0.0404	0.0330
47	Yes	0.9976	0.0628	0.0535
	No	0.9962	0.0769	0.0675

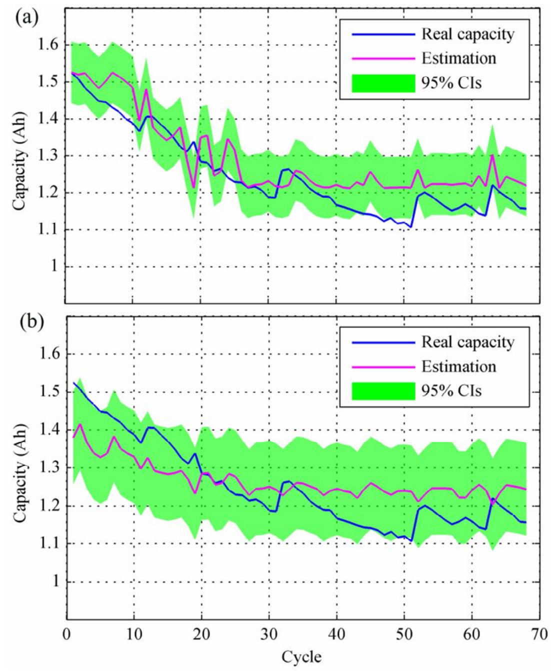

Fig. 6. Capacity estimation of battery 47 (a) considering ambient temperature; and (b) not considering ambient temperature

All the estimations considering AT are much closer to the real capacity than that not considering AT. The average value of MAE is 3.75% when considering AT, which is decreased by 20.7% than that not considering AT. Clearly, all the 95% confidence intervals (CIs) in the upper figures of Fig. 4 to Fig. 6 are narrower than that in the lower ones. Knowing narrower width means smaller variance and better reliability, thus this phenomenon indicates that the consideration of AT improves the precision of capacity estimation. Therefore, considering AT is a good way to significantly improve the precision and accuracy of capacity estimation.

In table 2, all RMSE of estimation considering AT are smaller than that not considering AT, and all the R^2 of the former are closer to 1 than the latter. More specifically, considering AT reduces the mean value of RMSE by 18.7% and improves the mean value of R^2 by 0.1%. Thus it's again demonstrated that considering AT can make the capacity estimation much more accurate and reliable.

Based on the above discussion, we may safely draw the conclusion that the CCCT can be used to estimate on-board capacity of lithium-ion batteries and the consideration of ambient temperature can improve the estimation result significantly.

4.3 Comparison

In order to validate the superiority of the proposed method, capacity is also estimated by back-propagation neural network (BPNN) [32] which consists of an input layer, a 5-neuron hidden layer and an output layer. In this network, sigmoid and linear transfer functions are used in the hidden layer and output layer respectively. The results are shown in Fig. 7, Fig. 8 and Fig. 9 and compared with our method in Fig. 10.

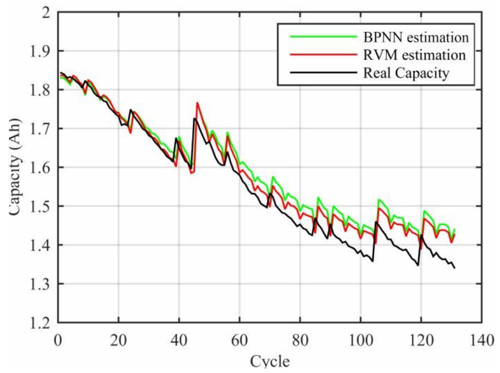

Fig. 7. Comparison of capacity estimation of battery 18 between RVM and BPNN methods

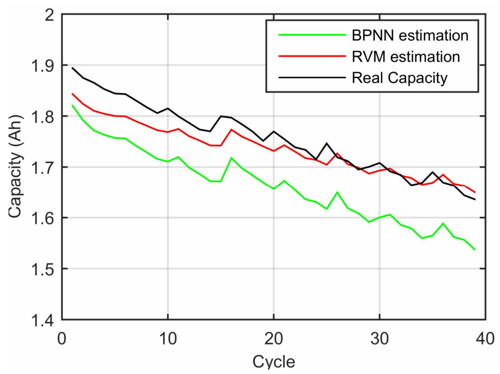

Fig. 8. Comparison of capacity estimation of battery 32 between RVM and BPNN methods

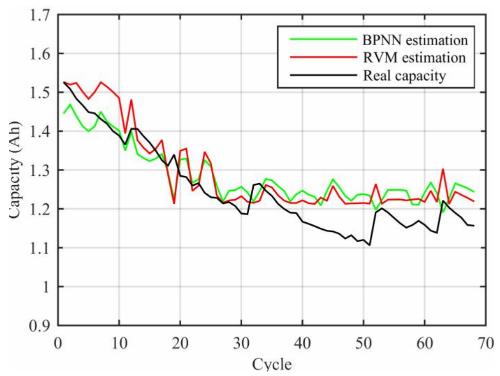

Fig. 9. Comparison of capacity estimation of battery 47 between RVM and BPNN methods

Fig. 10 illustrates that all the R^2 of the RVM are bigger than that of BPNN and both the RMSE and MAE are smaller than that of BPNN, and thus the RVM method is better than BPNN method when using the CCCT and AT as input, which is also validated by Fig. 7 to Fig. 9 as all the capacities estimated by RVM are much closer to the real one than the BPNN method.

Furthermore, capacity estimation made by an adaptive multi-kernel relevance machine (MKRVM) based on accelerated particle swarm optimization algorithm [27] is also compared with our method in table 3. It shows that both R^2 and RMSE of our method are larger than that of MKRVM, which indicates our method has a better overall

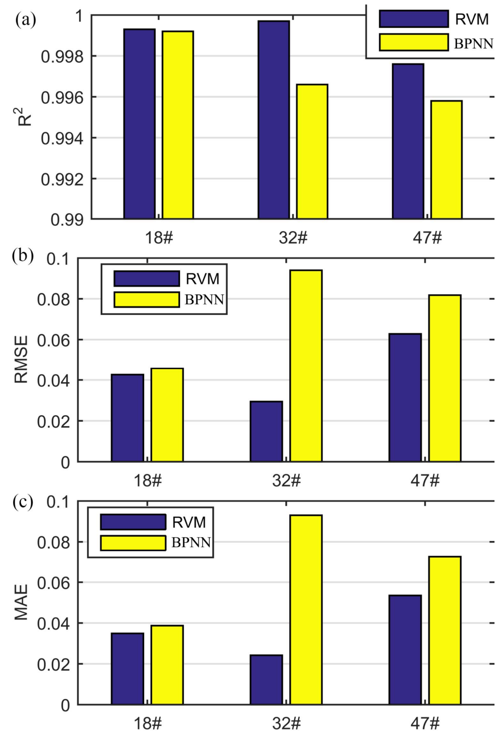

Fig. 10. Comparison of capacity estimation performance between RVM and BPNN methods

Table 3. Comparison result of capacity estimation between MKRVM and our method (RVM)

Battery	Method	R^2	RMSE	MAE (%)
18	MKRVM	0.9898	0.0155	/
	RVM	0.9993	0.0426	3.49
32	MKRVM	0.9870	0.0077	/
	RVM	0.9997	0.0294	2.42
47	MKRVM	0.7613	0.0149	/
	RVM	0.9976	0.0628	5.35

estimation performance while a little worse local estimation performance. However, some features used in reference [27] including time interval of equal discharge voltage difference and discharge cutoff voltage are not applicable in real application due to the dramatically dynamic condition in discharge phase as introduced before. Thus, considering the feasibility and accuracy, our method is still appealing for real application.

5. Conclusion

This paper suggests paying more attention on charge phase instead of discharge phase for on-board capacity estimation of lithium-ion batteries. It has been found that constant current charge time (CCCT) has a strong linear correlation with the capacity as long as the capacity is more than 80% of the battery's rated value, and CCCT is applicable for on-board capacity estimation, which is validated by experiment via relevance vector machine (RVM). Adding the ambient temperature (AT) into the RVM input dramatically improves the estimation precision, reliability and robustness. Based on the comparison result, RVM is superior to back-propagation neural network (BPNN) for estimating capacity. Therefore, the proposed method is promising for on-board capacity estimation of lithium-ion batteries.

Although RVM was used by others to estimate state of health (SOH) of batteries, our method pays more attention on charging phase, which is exactly our suggestion for future SOH estimation. Meanwhile, demonstrated by our research, CCCT can be replaced by the charging time between two certain voltages depending on the types of battery and using condition. It is worth noting that the proposed method can be applied when the batteries are recharged through widely used constant current-constant voltage (CC-CV) charging protocol. The developed method may not be applicable to batteries on hybrid electric vehicles (HEVs) which are under the control of complex energy management strategies. In the future, we will find other techniques to replace the complex RVM method.

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