Available online at www.ijpe-online.com

International Journal of Performability Engineering

vol. 14, no. 7, July 2018, pp. 1618-1627
DOI: 10.23940/ijpe.18.07.p26.16181627

Lithium-ion Power Batteries SOC Estimation based on PCA

Haiying Wang*, Yuran Wang, Zhilin Yao, and Zhilong Yu

College of Automation, Harbin University of Science and Technology, Harbin, 150080, China

Abstract

SOC is an important parameter of power batteries of electric vehicles. Its accurate estimation is vital to the correct implementation of the control strategy of the whole vehicle. It is strait to estimate SOC of the battery accurately using existing estimation methods. Aiming at the shortcomings in these methods, we proposed to establish an estimation model for battery SOC using principal component analysis (PCA) algorithm in this study. However, unable to extract non-linear factors in parameters, PCA algorithm would bring about an estimation error of battery SOC; thus, we proposed to establish an estimation model for battery SOC using kernel principal component analysis (KPCA) algorithm. The model was simulated and verified through experiments. After simulation, it shows that the improved model may adapt to a more complicated environment, meet the requirements of promptness and reliability, and has higher estimation accuracy with an average estimation error of 1.46%, which is better than that of Ah measurement method.

Keywords: state of charge (SOC); principal component analysis (PCA); kernel principal component analysis (KPCA)

(Submitted on April 1, 2018; Revised on May 15, 2018; Accepted on June 20, 2018)

1. Introduction

Estimating the remaining capacity of a battery (i.e. State of charge (SOC)) is one of the steps the most basic and vital in battery management. Precise and reliable estimation can provide accurate SOC for electric vehicle drivers, and also offers valuable references for the effective supervision of batteries [1]. Currently, ordinary domestic and foreign SOC estimation methods include Kalman filtering method, Ah measurement method, internal resistance method, extended Kalman filtering arithmetic and neural network arithmetic, etc.

Kalman filtering arithmetic is suitable for various batteries, and its estimation is relatively accurate [2]. However, it has a relatively high requirement on the equivalent circuit model of batteries. The accuracy of estimated results depends on the circuit model to a large extent. Uncertainties in the circuit model may result in big errors in estimation; for internal resistance method, it is not easy to measure the internal resistance of cells, and changes in internal resistance during the initial charge and discharge periods are large. Ah measurement method has an accumulative error; thus, its error is very big if the temperature is extremely high and current undulates violently [3-4]. Artificial neural network method needs a great amount of reference data for training, so it is greatly influenced by the training data and methods [5]. For Kalman filtering algorithm, limitations in computer word length would cause filtering divergence, which leads to inaccuracy of the model [6-7].

Factors considered in estimating the state of charge using the above methods and estimation models are often single and columbic efficiency, hysteresis and cycle life of batteries are not included, which leads to errors in the estimation of the state of charge. Moreover, these methods cannot meet the needs for real-time monitoring, varied environment and states. Thus, it fails to meet the requirement of precise and rapid detection for batteries in electric vehicle or hybrid electric vehicle system. The objective of this study is to set up an effective SOC estimation model for lithium-ion power batteries for electric vehicles [8]. Since power batteries have multiple variables and non-linear electric-chemical property, we analyzed the status data, which reflects the SOC of lithium-ion power batteries using mathematical statistics method. Based on reflecting the real-time characteristics of power batteries, we established an estimation model for the SOC of lithium-ion power batteries

* Corresponding author.
E-mail address: wanghy@hrbust.edu.cn

using PCA and KPCA methods. The paper provides theoretical and technical support for the simulation test of conventional performance of batteries, assesses the key performance relevant to power batteries, and evaluates of reliability and safety of power batteries in the actual vehicle operating process [9-11].

2. Introduction of PCA and KPCA Principles

2.1. PCA Principle

Assume that in the problem to be solved, there are p random variables, and they are expressed as $X_1, X_2, \ldots, X_p$ respectively. The main idea of PCA is to conduct linear transformation on these original variables and obtain their linear combination. $F_1, F_2, \ldots, F_k$ ($k \le p$) are new variables after transformation, and are independent from each other. Keep most of the valuable data among the initial parameters; some redundancies and obstructions between various variables are eliminated [12]. Therefore, the main aim of PCA is to attempt to find a linear combination F_i that can represent original variables; its form of expression is shown in equation (1).

$$\begin{cases} F_1 = u_{11}X_1 + u_{12}X_2 + \ldots + u_{1p}X_p, \\ F_2 = u_{21}X_1 + u_{22}X_2 + \ldots + u_{2p}X_p, \\ \ldots\ldots \\ F_p = u_{p1}X_1 + u_{p2}X_2 + \ldots + u_{pp}X_p \end{cases} \tag{1}$$

According to the basic principle of the principal component analysis, the above equation should meet the following conditions:

1. The quadratic sum of coefficients that constitute any principal component is 1, that is:

$$u_{i1}^2 + u_{i2}^2 + \ldots + u_{ip}^2 = 1 \tag{2}$$

2. All the principal components are independent from each other, that is to say, there is no overlap information between the principal components, meeting the following requirement:

$$\mathrm{cov}(F_i, F_j) = 0, i \ne j, i, j = 1, 2, \ldots, p \tag{3}$$

3. The variance of the main components should decrease progressively and successively based on different importance degrees of them, that is they should meet the following requirement:

$$Var(F_1) \ge Var(F_2) \ge \ldots \ge Var(F_p) \tag{4}$$

2.2. Principle of KPCA

We took $x_1, x_2, \ldots, x_m$ as the sample set to be trained, and expressed the input space as $\{x_i\}$. The KPCA method is to map $\{x_i\}$ to a higher dimensional space (characteristic space) from the dimensional space where it locates, and then conduct relevant PCA operations in the higher dimensional space [13]. Regard Φ as the corresponding mapping; its definition is as follows:

$$\begin{aligned} \Phi &: R^d \to \mathcal{F} \\ x &\mapsto \xi = \Phi(x) \end{aligned} \tag{5}$$

Where Rd is d-dimensional Euclidean space and the dimensional space where the original data {xi} locate. It is usually known as input space [14-15]. After the original data are mapped, the space where it exists is the Hilbert space F, also called characteristic space.

Under the condition that kernel function has been transformed, map the original data marker *x* to be transformed on the mapping *Φ* to *F*. The data obtained through this transformation meets the centralization condition in the characteristic space, that is:

$$\sum_{\mu=1}^{M} \Phi(x_\mu) = 0 \tag{6}$$

The obtained covariance matrix in this characteristic space is:

$$C = \frac{1}{M}\sum_{\mu=1}^{M} \Phi(x_\mu)\Phi(x_\mu)^T \tag{7}$$

Let λ be the eigenvalue of *C*, and *v* be the corresponding eigenvector, we have:

$$\begin{aligned} &V \in F \setminus \{0\} \\ &Cv = \lambda v \end{aligned} \tag{8}$$

That is to have:

$$(\Phi(x_v)\cdot Cv) = \lambda(\Phi(x_v)\cdot v) \tag{9}$$

This can prove that $\Phi(x_1)$, $\Phi(x_2)$,…, $\Phi(x_M)$can represent all eigenvectors linearly, that is

$$v = \sum_{i=1}^{M} \alpha_i \Phi(x_i) \tag{10}$$

Then, we have

$$\frac{1}{M}\sum_{\mu=1}^{M}\alpha_\mu(\sum_{w=1}^{M}(\Phi(x_v)\cdot\Phi(x_w)\Phi(x_w)\Phi(x_\mu))) = \lambda\sum_{\mu=1}^{M}(\Phi(x_v)\cdot\Phi(x_\mu)) \tag{11}$$

Where v=1, 2,…,M. Define $M\times M$ dimensional matrix *K* as:

$$K_{\mu v} := (\Phi(x_\mu)\cdot\Phi(x_v)) \tag{12}$$

Then equation (11) can be simplified as:

$$M\lambda K\alpha = K^2\alpha \tag{13}$$

Obviously,

$$M\lambda\alpha = K\alpha \tag{14}$$

Solve equation (14) to obtain eigenvalues and eigenvectors. In the eigenvector space V^k, the test sample projection is as follows.

$$(v^k\cdot\Phi(x)) = \sum_{i=1}^{M}(\alpha_i)^k(\Phi(x_i),\Phi(x)) \tag{15}$$

Replace the inner product with a kernel function, and then we have

$$(v^k\cdot\Phi(x)) = \sum_{i=1}^{M}(\alpha_i)^k K(x_i, x) \tag{16}$$

If equation (6) is false, it is necessary to make adjustments

$$\Phi(x_\mu) \to \Phi(x_\mu) - \frac{1}{M}\sum_{v=1}^{M}\Phi(x_v) \tag{17}$$

Then, the kernel matrix can be corrected as

$$K_{\mu v} \to K_{\mu v} - \frac{1}{M}(\sum_{w=1}^{M}K_{\mu w} + \sum_{w=1}^{M}K_{wv}) + \frac{1}{M^2}\sum_{w,\tau=1}^{M}K_{w\tau} \tag{18}$$

3. Establishment of SOC Estimation Model Using PCA

Considering the restrictions of laboratory conditions, it is difficult to do measurements under continuously changing temperature *T*. We can only maintain the temperature T within a certain range and measure the relationship between *T* and *SOC* by stages [16-18]. This relationship is reflected by measuring the relationship between operating voltage *V* and *SOC*. When the temperature ranges from 15 to 55℃, the influence of temperature on *SOC* is basically the same, so we estimated *SOC* by measuring the influences of other battery performance parameters on *SOC* at room temperature. The curve on the relationship between battery cycle number *n* and *SOC from experiment shows* their relationship is roughly nonlinear [19-21]. Here, we did not consider the influence of the cycle number *n*; instead, we assumed that all batteries were the newest, and the influence of *n* on *SOC* could be neglected. Based on the above factors, we established an estimation model for battery SOC according to the following procedure [22].

Step 1: To reduce the influence of dimension and the difference in the order of magnitudes, we need to subtract the average value in the column where the component locates from each component. We need to conduct zero-mean transformation on the data using the Z-score method (zero-mean method), and conduct standardized transformation on the transformed matrix. See details in equation (19) to (21).

$$X^T = (X_1, X_2, ..., X_p) = \begin{pmatrix} x_{11} & x_{12} & ... & x_{1p} \\ x_{21} & x_{22} & ... & x_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & ... & x_{np} \end{pmatrix} \tag{19}$$

$$x_{ij}^* = x_{ij} / s_j, s_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_{ij} - \bar{X}_j)^2} \\ i = 1, 2, ...n; \; j = 1, 2, ..., p \tag{20}$$

$$\bar{X}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \quad i = 1, 2, ...n; \; j = 1, 2, ..., p \tag{21}$$

Where $\bar{X}_j$ and s_j respectively represent the sample average value and standard deviation of the j^{th} index, x_{ij} is the original data of the i^{th} monitoring point of the j^{th} index, and x_{ij}^* is the new data obtained after the dimension is eliminated.

Step 2: Obtain the covariance matrix of X^* after the dimension is eliminated.

$$\Sigma_x = \begin{bmatrix} Cov(X_1^*, X_1^*) & Cov(X_1^*, X_2^*) & ... & Cov(X_1^*, X_p^*) \\ Cov(X_2^*, X_1^*) & Cov(X_2^*, X_2^*) & ... & Cov(X_2^*, X_p^*) \\ ...... & & & \\ Cov(X_p^*, X_1^*) & Cov(X_p^*, X_2^*) & ... & Cov(X_p^*, X_p^*) \end{bmatrix} \tag{22}$$

Step 3: Obtain eigenvalues and their corresponding eigenvectors according to the above covariance matrix Σ_x, and sort the eigenvalues in descending order, written as $\lambda_1 > \lambda_2 > ... > \lambda_p$. Adjust their corresponding eigenvectors, which can be written as $u_1, u_2, ..., u_p$, where $u_i = (u_{i1}, u_{i2}, ..., u_{ip})^T$.

Step 4: Calculate the accumulative dedication rate according to the result obtained above, and give the proper number of principal components.

$$F_i = U_i^T X \quad i = 1, 2, ..., k (k \le p) \tag{23}$$

Step 5: Conduct least square regression modeling using the obtained principal components, and obtain the needed model curve.

Obtain the eigenvalues and their corresponding eigenvectors according to step 1 to step 3. Based on voltage V_o, DC internal resistance R and electric current I, data are shown in Table 1.

Table 1. Numerical values of eigenvalues and eigenvectors

Eigenvalue	Eigenvector
1.9080	0.6067 0.7005 0.3757
0.9676	0.5097 0.01987 -0.8601
0.1244	0.6100 -0.7133 0.3450

Calculate the dedication rates and accumulative dedication rates of each principal component according to step 4. The eigenvalues and dedication rates are shown in Table 2.

Table 2. Reference table of dedication rates and accumulative dedication rates of eigenvalues

Eigenvalue	Dedication rate (%)	Accumulative Dedication rate(%)
1.9080	0.6360	0.6360
0.9676	0.3225	0.9585
0.1244	0.0415	1

According to the table above, the principal component dedication rate of the first two standardized samples has reached 95.85%. According to the calculating rule of principal components, the accumulative dedication rates of the first two main ingredients meet the requirement; thus, we only need to take the first two principal components.

According to step 5, conduct the least square regression modelling using the obtained principal components to get the SOC estimation model, as shown in equation (24):

$$\begin{aligned} SOC_{PCA} &= 3.4723 + \left[0.0332 \;\; -0.6233 \;\; -22.5608\right] \\ &.*\left[I \quad V_o \quad R\right]^T \end{aligned} \tag{24}$$

Where $\left[I \quad V_o \quad R\right]^T$ is the vector constituted by I, V_o and R.

4. Establishment of SOC Estimation Model Using KPCA

Step 1: Combine the data to be analyzed into a multidimensional data matrix. The matrix consists of n variables, each of which includes m samples i.e.

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix}$$

Step 2: Calculate the kernel matrix *K*. Select the Gaussian radial kernel function, and obtain the needed kernel matrix according to equation (12) based on the parameters.

Step 3: Obtain KL by correcting the kernel matrix according to equation (18).

Step 4: Calculate the eigenvalues of the kernel matrix KL $\lambda_1,...,\lambda_n$ and their corresponding eigenvectors $v_1,...,v_n$ using Jacobi iterative method, and sort the eigenvalues in descending order, written as $\lambda_1^{'} > ... > \lambda_n^{'}$, and adjust their corresponding eigenvectors, written as $v_1^{'},...,v_n^{'}$.

Step 5: Conduct the unit orthogonalization for eigenvectors using Schmidt orthogonalization, to obtain $\alpha_1,...,\alpha_n$.

Step 6: Calculate the accumulative dedication rates $B_1,...,B_n$ successively according to the obtained eigenvalues, and then provide the calculated amount of vital constituent, written as $\alpha_1,...,\alpha_t (t \le n)$

Step 7: Calculate the cast on the eigenvector $Y = KL \cdot \alpha$ on the basis of the corrected kernel matrix KL and the main component $\alpha = (\alpha_1,...,\alpha_t)$ obtained in the previous step. Then, the obtained *Y* is the final data obtained using KPCA method.

Step 8: Conduct the least square regression modelling according to the finally obtained data *Y*, and get the final SOC estimation model.

On the basis of the KPCA steps, establish the estimation model of SOC:

Obtain the characteristic values and their corresponding feature vectors of unit orthogonalization according to step 1 to step 5, by using voltage V_o, DC inner resistance *R* and electric current *I*, as displayed in Table 3.

Table 3. Numerical values of characteristic values and feature vectors

Eigenvalue	Eigenvector		
1.9466	0.6998	0.7069	0.1028
0.9988	-0.1412	0.0042	-0.9900
0.0545	-0.7002	0.7073	-0.0969

Calculate the dedication rate and accumulative dedication rate of each principal component according to step 6. Eigenvalues and dedication rates are shown in Table 4.

Table 4. Reference table of dedication rates and accumulative dedication rates of characteristic values

Eigenvalue	Dedication rate(%)	Accumulative Dedication rate(%)
1.9466	0.6489	0.6489
0.9988	0.3329	0.9818
0.0545	0.0182	1

According to Table 4, the principal component dedication rate of the first two standardized samples has reached 98.18%. According to the calculating rule of principal components, the accumulative the dedication rate which is provided by the first two main ingredients satisfied the requirement; thus, we only need to take the first two principal components.

According to step 7, get the final data needed, and in accordance with step 8, conduct the least square regression modelling through the obtained data to get the SOC estimation model when $T = 15 \sim 55℃$, as shown below:

$$SOC_{KPCA} = 1.9871 + [0.0086 \;\; -0.1683 \;\; -23.3239] .* [I \;\; V_o \;\; R]^T \tag{25}$$

Where $[I \;\; V_o \;\; R]^T$ is the vector constituted by *I*, V_o and *R*.

5. Simulation and Experimental Verification of the Model

So, as to verify the estimation property of the model of battery SOC of PCA algorithm and KPCA algorithm under a normal temperature condition, a pulse discharge experiment was designed with the experimental temperature controlled by a thermostat; all temperature deviations are controlled at±2℃. The total number of sampling data points was 7,800; the sampling interval and the sampling time using Ah measurement method were both 1s. In other words, the total data size was 7,800 sets of data. The obtained curves on changes in sampling current, voltage and temperature of the battery are respectively shown in Fig. 1 to Fig.3. Fig. 4 expresses the comparative analysis of SOC estimation, and Table 5 shows the comparison between errors of estimation results from PCA and Ah measurement methods at room temperature.

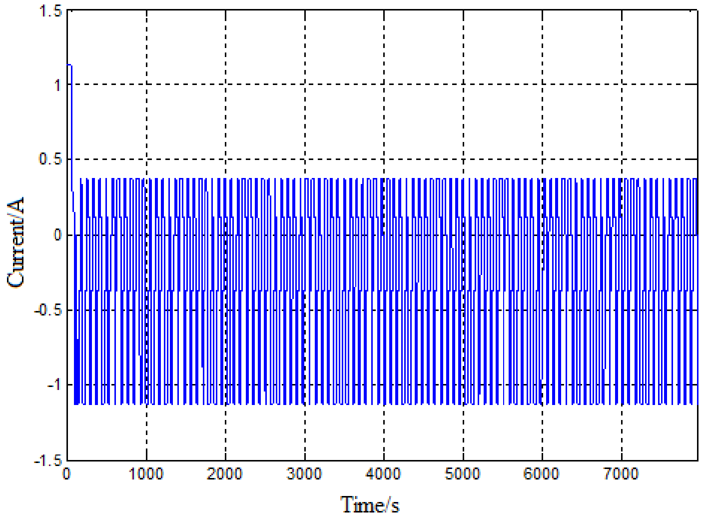

Figure 1. Curve on changes in sampling current

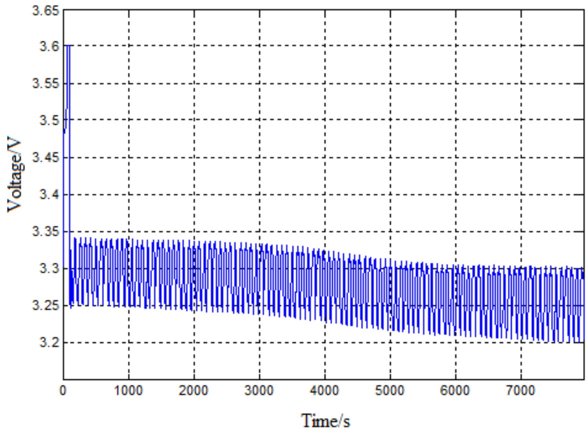

Figure 2. Curve on changes in sampling voltage

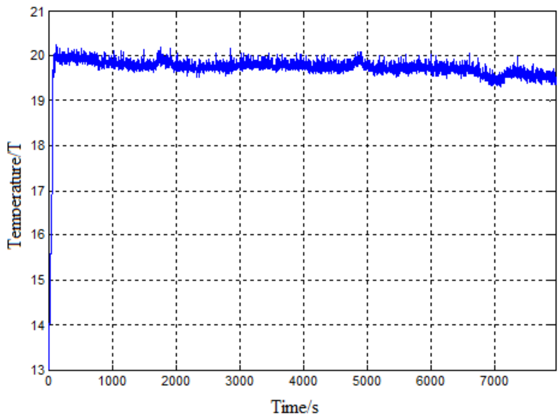

Figure. 3 Curve on changes in temperature

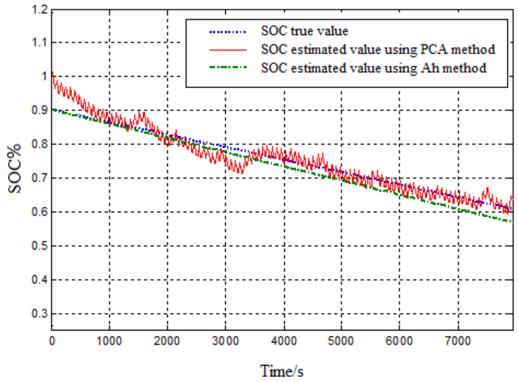

Figure 4. Comparative analysis of SOC estimation

Table 5. Comparison between errors in estimation results using PCA and Ah measurement method at room temperature

Algorithm	Maximum deviation	Root-mean-square deviation	Average estimation deviation
Ah measurement method	5%	0.0263	2.37%
PCA method	8%	0.0230	2.29%
Deviation improvement	-3%	0.0033	0.08%

According to the above analysis, the SOC estimation model of PCA method is better than the Ah measurement method to some extent, but its advantage is tiny. The reason why the expected effect is not ideal enough for estimation of the SOC may be that many linear relationships are considered in data analysis of parameters that affect SOC while non-linear relationships between variables are not considered. Therefore, we established the estimation model using KPCA algorithm. Fig. 5 shows the SOC estimation curve using KPCA method at normal temperature.

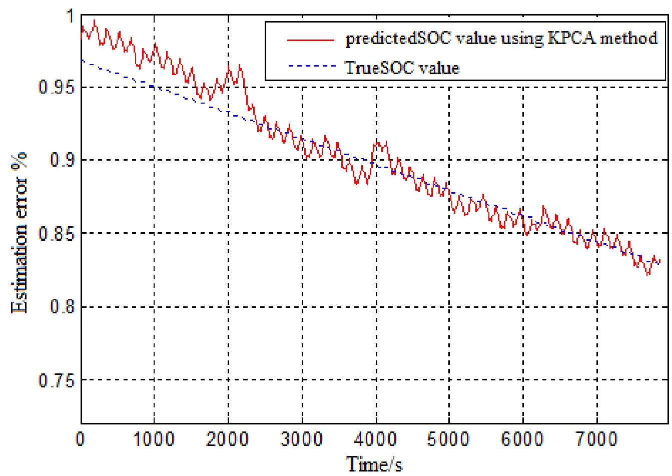

Figure 5. SOC estimation curve using KPCA method at normal temperature

Table 6. Comparison between errors of estimation results from KPCA and PCA at normal temperature

Arithmetic	Maximal calculation deviation	Root-mean-square error	Average calculation deviation
KPCA	3.54%	0.019	1.46%
PCA	8%	0.023	2.29%
Deviation reduction	4.46%	0.004	0.83%

6. Conclusions

From the perspective of multi-variable prediction of the battery SOC, we analyzed the state parameters that could reflect the SOC of lithium-ion power batteries, and established a SOC estimation model based on PCA and its improved algorithm. On the basis of reflecting the real-time features of power batteries, this model can accurately estimate the SOC, and during realistic manufacture offer theoretical and technical support. The conclusions we can obtain are shown in the next paragraph:

1. The estimation model of battery SOC has been established using PCA algorithm and least square regression method. The experiment verifies that this model is practical, with an estimation accuracy of 2.29%, which is better than the estimation model of Ah measurement method.

2. Since non-linear factors in parameters cannot be extracted using PCA algorithm, we proposed to establish the SOC estimation model using KPCA algorithm. The experiment verifies that the prediction precision of this model is 1.46%, which is higher than that of the PCA estimation model. Thus, this model can provide reference and guidance for the prediction of SOC.

Acknowledgements

This work is supported by the National Key Research and Development Program of China (2016YFC0300104), Advance Research Project of Weapon Equipment (41421040301) and Technological Innovation Foundation for Youth Reserve Talents of Disciplines in Science of Harbin (2017RAQXJ069).

References

1. Z. L. Yu, Y. L. Guo, H. Y. Wang, "Research on state of charge estimation of Li-ion battery based on SCKF-STF", Electric Machines & Control, Vol.17,No.10,pp.70-76,2013.
2. H. Liu, "Research on SOC estimation method of Lithium Ion Battery for Electric vehicle based on KEF", Master thesis of Beijing Jiaotong University, Vol.8, No.5, pp.195-199, 2010.
3. S. J. Lee, J. H. Kim, J. M. Lee, and B. H. Cho, "The State and Parameter Estimation of an Li-Ion Battery Using a New OCV-SOC Concept", Power Electronics Specialists Conference. IEEE, pp.17-21, 2007.
4. G. C. Li, H. Jiang, H. Y. Wang, "The SOC Compute Model of Batteries Based on Fuzzy Neural Network", Journal of Test & Measurement Technology Vol.21,No.5,pp.405-409,2007.
5. B. J. Liu, Y. Wang, T. M. Yin, "Electric vehicle Battery Management system", electric automatization, Vol.32,No.1,pp.60-62,2010.
6. J. Kim, G. S. Seo, C. Y. Chun, et al, "OCV Hysteresis Effect-based SOC Estimation in Extended Kalman Filter Algorithm for a LiFePO4/C Cell", Electric Vehicle Conference (IEVC),pp.4-8,2012.
7. N. A. Windarko, J. Choi, G. B. Chung, "SOC Estimation of LiPB Batteries Using Extended Kalman Filter Based On High Accuracy Electrical Model", Power Electronics and ECCE Asia (ICPE & ECCE), pp.2015-2022,2011.
8. G. Z. Wang, H. Ye, "Principal component Analysis and partial least Square method". Beijing: Tsinghua University Press, pp.7-9, 2012.
9. W. Ding, F. U. Yongqing, "Automatic target recognition based on kPCA feature extraction algorithm", Applied Science & Technology, Vol.38, pp.1-2, 2011.
10. R. Li, G. C. Li, Z. L. Yu: "Study on safety technology of high - power lithium power battery", National Conference on Chemistry and physical Power supply, 2015.
11. D. U. Zhuo-Ming, T. U. Hong, "KPCA method research and application process", Computer Engineering & Applications, Vol.46, No.7, 2010.
12. Q. Jia, Y. Zhang, Y. Guan, et al, "Fault Diagnosis of Nonlinear Systems Based on Analytical Models: A Survey", Information & Control, Vol.41, No.3, pp.356-364, 2012.
13. R. LI, J. F. WU, H. Y. Wang, et al, "A Design Method of CAN BUS Network Communication Structure for Electric Vehicle", Journal of Harbin University of Science & Technology, Vol.17,No.1,pp.68-73,2012.
14. J. Chatzakis, K. Kalaitzakis, N. C. Voulgaris, and S. N. Manias, "Designing a New Generalized Battarry Management System", IEEE Trnations on Industrial Electronics, Vol.50, No.5, pp.990-999, 2003.
15. F. Feng, K. Song, R. Lu, et al. "Equalization Control Strategy and SOC Estimation for LiFePO_4 Battery Pack", Transactions of China Electrotechnical Society, Vol.30,No.1,pp.22-29,2015.
16. Tu Y, Lin Y, Wang J, et al, "Semi-Supervised Learning with Generative Adversarial Networks on Digital Signal Modulation Classification," CMC-Computers Materials & Continua, Vol. 55, No. 2 pp. 243-254, 2018.
17. C. X. Lv, X. R. Li, L. H. Hu, et al. "A Smoothing Strategy for Hybrid Energy Storage System Based on Wavelet Frequency Allocation and Two-level Fuzzy Control", Automation of Electric Power Systems, Vol.39,No.2,pp.21-29,2015.
18. Y. Lin, X. Zhu, Z. Zheng, et al. "The individual identification method of wireless device based on dimensionality reduction and machine learning", Journal of Supercomputing, No.5, pp.1-18, 2017.
19. Y. Lin, C. Wang, J. X. Wang, Z. Dou. "A Novel Dynamic Spectrum Access Framework Based on Reinforcement Learning for Cognitive Radio Sensor Networks", Sensors, Vol.16, No.10, pp.1-22, 2016.

20. Y. Lin, C. Wang, C. Ma, et al. “A new combination method for multisensor conflict information”, Journal of Supercomputing, Vol.72, No.7, pp.2874-2890, 2016.
21. Q. Wu, Y. Li, Y. Lin, “The application of nonlocal total variation in image denoising for mobile transmission”, Multimedia Tools & Applications, Vol.76, No.16, pp.1-13, 2016.
22. C. Shi, Z. Dou, Y. Lin, et al. “Dynamic threshold-setting for RF-powered cognitive radio networks in non-Gaussian noise”, Physical Communication, Vol.27, No.4, pp.99-105, 2018.