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State of charge estimation of lithium-ion batteries using optimized Levenberg-Marquardt wavelet neural network

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ABSTRACT

State of charge (SOC) is one of the most critical parameters for indication of the remaining energy which is vital important for the safety and reliability of power system. In this paper, Levenberg-Marquardt (L-M) algorithm optimized multi-hidden-layer wavelet neural network (WNN) model and a series of novel intelligent SOC estimation methods using L-M based WNN are proposed. Particle swarm optimization (PSO) algorithm is used to optimize L-M based three-layer WNN (LMWNN) for SOC estimation problem. Furthermore, it is validated that L-M based multi-hidden-layer WNN (LMMWNN) has better performance than LMWNN. Basing the specific characteristic of SOC estimation, the LMMWNN method is optimized by combining piecewise-network method (PLMMWNN) and seven-point linear smoothing method (smoothed PLMMWNN). Under single driving cycle, such as the New European Driving Cycle(NEDC), the mean absolute error of PLMMWNN can be decreased to 0.6% and the maximum absolute error 5%. A comparison study of the series of WNN-based methods with BP neural network (BPNN) and extend Kalman filter (EKF) is conducted. The robustness evaluation, which is based on untrained driving cycles test, measurement noise test and piecewise training and batteries test, indicates the good performance on estimation accuracy, applicability and robustness of the proposed methods.

1. Introduction

With the rapid development of electric vehicle (EV), lithium-ion batteries play a more and more important role due to their advantages of high energy density, high cell voltage, long lifespan, no memory effect and low self-discharge rate [1]. To guarantee the EV performance, it has high requirements on the battery management system (BMS). BMS is in charge of monitoring complete information of batteries such as current, voltage and temperature to ensure safety and reliability of the power system [2]. State of charge (SOC) is one of the most critical parameters for indication of the remaining energy and it is regarded as the most key parameter of BMS [1,3]. Accurate SOC estimation is of vital importance to prevent the batteries from over-charging or over-discharging, which has great influence on service safety and service life of batteries. In addition, the accuracy of SOC estimation has direct effect on reliability and validity of BMS. Unfortunately, SOC cannot be measured directly and is related to amount of factors, such as current rate, ambient temperature, parameter uncertainties, battery degeneration and external disturbance [1]. Therefore, the study of estimation algorithm to obtain the approximate value of SOC using measureable variables (e.g., current, voltage and temperature) is of great significance [4].

Accompanied with the deeper research on SOC estimation, a number of approaches have been proposed, such as Ampere-hour (A·h) integral or Coulomb counting method [5,6], open-circuit voltage method [7], Kalman filter (KF)-based methods (e.g., extend Kalman filter (EKF) [8,9], unscented Kalman filter (UKF) [10,11] Cubature Kalman Filter (CKF)), particle filter(PF) [12,13], sliding mode observer (SMO) [14,15] and artificial neural networks(ANNs) (e.g., back-propagation neural network (BPNN) [16,17], radial neural network (RNN) [18], support vector machine (SVM) [19] network and wavelet neural network (WNN) [20,21]). For the first three methods, battery models are not necessary to establish and the estimation processes are easy to implement. However, despite the simplicity, these non-model based and open-

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Nomenclature

A·h	Ampere-hour
ANNs	Artificial neural networks
BMS	Battery management system
BP	Back-propagation (neural network)
BPNN	Back-propagation neural network
CKF	Cubature Kalman Filter
EKF	Extend Kalman filter
EUDC	Extra Urban Driving Cycle
EV	Electric vehicle
HPPC	The hybrid power pulse characteristics
KF	Kalman filter
L-M	Levenberg-Marquardt
LMBP	Levenberg-Marquardt based back-propagation (neural network)
LMMWNN	Levenberg-Marquardt based multi-hidden-layer wavelet neural network
LMWNN	Levenberg-Marquardt based three-layer wavelet neural network
NEDC	New European Driving Cycle
OCV	Open-circuit voltage
PF	Particle filter
PLMMWNN	Piecewise-network Levenberg-Marquardt based multi-hidden-layer wavelet neural network
PSO	Particles swarm optimization
PSOLMWNN	Particles swarm optimization method optimized Levenberg-Marquardt based wavelet neural network
RNN	Radial neural network
SMO	Sliding mode observer
SOC	State of charge
SVM	Support vector machine
UDDS	Urban Dynamometer Driving Schedule
UKBC	the United Kingdom Bus Cycle
UKF	Unscented Kalman filter
WNN	Wavelet neural network

loop methods cannot meet the demand of precision which is caused by inaccurate initialization of SOC, measurement noise and external disturbance. Therefore, close-loop and model based methods are the main direction of recent studies.

Despite requiring higher computation cost than A•h method, KF, PF and SMO are increasingly popular due to their merits in being self-correcting, the availability of the dynamic SOC estimation error range. Basing many important proposed battery models, such as the equivalent circuit model [22–24], the electrochemical model [25] and electrical thermal model [26], the performance of model based methods improves greatly. As the expansions of the KF method, EKF and UKF methods are widely used in SOC estimation on account of the satisfying results in terms of accuracy and robustness against measurement noise. Nevertheless, there are some shortcomings in the application process of KF-based methods. For instance, the EKF cannot avoid the problems of large linearization errors and the Jacobian matrix computation, which may cause the filter invalid and estimation accuracy reduced for highly nonlinear battery systems [15]. The UKF has been validated to have a higher accuracy in estimating SOC than the EKF and it is not required to calculate the complicated Jacobian matrix [27–29]. The CKF method is also a kind of KF-based SOC estimation method and it is considered to be more efficient and stable than UKF [30,31]. However, the KF-based methods are in fundamentally based on an assumption that the noise is Gaussian white noise and the statistic property of the system and measurement noises, which is represented as covariance, should be known. The SMO is a reliable and robust method for SOC estimation in terms of model error and external disturbance [14,15]. Nevertheless, the optimal parameters of SMO are hard to obtain which brings the process of SOC estimation some trouble. The PF method requires a large number of particles and massive matrix operations which limits its application to SOC estimation. In our previous studies, a modified model based UKF SOC estimation method [32] and a comparison study [33] on two model-based adaptive algorithms for SOC estimation (adaptive-UKF and adaptive-SMO) are given. Furthermore, a nonlinear observer-based algorithm [34,35] has been developed to efficiently estimate the SOC of batteries. However, with the further study on the model-based methods, it is found that using more measurable variables to obtain the estimated SOC will make the model or computation and experimental process more complex. Moreover, for highly nonlinear battery systems, it is fairly difficult using one specific model to describe the characteristics of batteries in most using conditions. For instance, the KF-based method using the second-order RC equivalent circuit model to estimate SOC firstly should identify not only the parameters such as a resistor R_0 and two parallel resistor-capacitor networks connected in series (R_1, C_1), (R_2, C_2) but also the certain relationship between open-circuit voltage (OCV) and SOC at the same temperature. The hybrid power pulse characteristics (HPPC) experiment and OCV-SOC relationship experiment are expected to conduct but cost much time and large expenses. Moreover, most KF-based methods only discuss about the discharge process of batteries on account of the RC parameters in discharge process different from the ones in charge process. In practical applications these also increase the complexity of data collection.

ANNs methods [36–38] do not require the detailed knowledge of battery systems and are a kind of high applicability way which can estimate SOC of different types of batteries and in different using conditions. ANNs based SOC estimation methods are normally regarded as non-model based or open-loop methods like A•h or open-circuit voltage methods [1,39]. Nevertheless, this paper thinks it is not accurate to simply think that ANNs methods are non-model based because ANNs methods are based on a complex mathematics model. The parameters of ANNs cannot reflect the specific characteristics of batteries directly but can well express the mapping relationships between measurable variables and SOC. ANN is essentially a kind of mathematical method to approximate the non-linear relationships among battery variables using its universal mathematics model. That is to say, a well-trained ANN itself is a model of batteries and the SOC estimation problem is essentially a nonlinear system identification problem. Due to the high applicability, foundation of mathematics model and intelligent properties, ANNs methods can overcome the problems of non-model based methods and physical model-based methods to some extent. Therefore, the researches on ANNs based SOC estimation methods are deepening in recent years. WNN is one of the attractive artificial neural networks because it integrates wavelet decomposition property with self-learning and nonlinear function approximation ability of ANNs [40]. The high accuracy and ability of detail description make the WNN have superiority in the field of SOC estimation comparing with other ANNs.

There are some researches on WNN. A self-recurrent WNN is proposed to help the PID control which has good performance in