A Novel State Estimation Approach Based on Adaptive Unscented Kalman Filter for Electric Vehicles

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ABSTRACT Accurately estimating the state-of-charge (SOC) of battery is of particular importance for real-time monitoring and safety control in electric vehicles. To obtain better SOC estimation accuracy, a joint modeling method based on adaptive unscented Kalman filter (AUKF) and least-squares support vector machine (LSSVM) is proposed. This article improves the accuracy of SOC estimation from four aspects. Firstly, the nonlinear relationship between SOC, current, and voltage is established by LSSVM. Secondly, a novel voltage estimation method based on improved LSSVM is proposed. Thirdly, the measurement equation of the novel AUKF is created by the improved LSSVM. Finally, the effectiveness of the proposed model is verified under different driving conditions. The comparison results show that the model can improve the accuracy of voltage and SOC estimation, and the SOC estimation error is controlled within 2%.

INDEX TERMS State-of-charge (SOC), adaptive unscented Kalman filter (AUKF), terminal voltage, least squares support vector machine (LSSVM).

I. INTRODUCTION
With the large-scale popularization of new energy electric vehicles (EVs), lithium-ion batteries (LIBs) have a longer cycle life, no memory effect in the process of charging and discharging, and no pollution to the environment in the process of production and recycling [1]–[4] are widely used. Although the LIBs have many advantages, the chemical properties of the LIBs are relatively active, and the side reactions in the process of charging and discharging will generate heat, which may cause potential safety hazards. Battery management system (BMS) can not only provide the driver with the accurate working state of the battery, but also provide the driver with the dynamic control of the energy storage system. State of Charge (SOC) is one of the most important parameters in BMS, accurate estimation of the SOC can prolong the life of the battery cell and improve the utilization rate of EVs [5]. However, due to the external factors such as accuracy of acquisition equipment, load, voltage, and temperature difference in the battery, it is difficult to estimate SOC with a specific mathematical model. Therefore, it is of great importance to building an accurate SOC estimator for vehicle stability and reliability [6].

Nowadays, a wide variety of SOC estimation algorithms have been developed to upgrade the performance of the SOC estimator [7]. The common methods include the ampere-hour counting method [8], open-circuit voltage method (OCV) [9], internal resistance methods [9]–[10], and model-based methods [11]. It is easy to realize for SOC online estimation by ampere-hour integration method, however, the initial capacity of the battery, time error, and current sensor cause error accumulation and reduce the accuracy of the SOC estimation. For OCV estimation, the OCV has an approximately linear relationship with SOC, which can get a higher accuracy of SOC estimation. However, in order to obtain a steady OCV, the batteries need to stand for a long time, therefore, this method is not suitable for online SOC estimation of EVs. The SOC can also be estimated by the internal resistance method. However, a large number of impedance experiments are needed to complete SOC estimation, the effect of SOC estimation is not ideal.

In order to reduce the estimation error of SOC, many model-based methods are studied [12]–[17]. Smith et al. [12] and Fang et al. [13] used partial differential equations to
establish an electrochemical model to complete SOC estimation; Sun et al. [14] proposed that the electrochemical model can obtain various characteristics of the LIBs, but there are some shortcomings, such as difficult calculation, complex parameter acquisition, and poor practicability; Reference [15] established series-based battery charge equalization systems to estimate the SOC of battery cells during the equalization process; Han et al. [16] proposed the module-based SOC estimation algorithm to estimate the cell SOC evolution and achieved good results, but the SOC accuracy relies on the simulation of the mathematical models; Samadi et al. [17] proposed the new Kalman filter (KF) model based on Takagi Sugeno fuzzy system to estimate SOC. The KF methods have a closed-loop correction structure, which can solve the problem of initial SOC value error, and it does not need the large data set to train the battery model, so it has been widely used. For the nonlinear system, the extended KF (EKF) and unscented KF (UKF) are applied in reference [1], [18]–[24], and the estimation results show the effectiveness of the algorithms. However, EKF uses the Taylor formula to expand the equation but ignores the higher-order term, which will lead to the inaccuracy of SOC estimation. UKF transforms the approximate linear function to the probability density function by using the unscented transformation (UT), the results show that UKF is more accurate and easier to implement than EKF. However, the noise covariance in UKF is set by human experience, which may lead to the divergence of filtering results. Therefore, the adaptive UKF algorithm is used to adjust the noise covariance of the system and improve the accurate estimation of state variables.

To improve the battery model estimation performance, an increasing number of data-driven approaches have also been used in recent years. The neural network (NN) is the most widely studied data-driven method and has achieved considerable success in SOC estimation [25]–[28]. He et al. [25] proposed the RBF neural network model for SOC estimation to eliminate the degradation effect of batteries. Reference [27] presented a joint model based on NN and UKF to estimate SOC, the experimental results show that this method can get an accurate SOC estimation under different experimental conditions. Reference [14] proposed that the electrochemical equalization process; Han et al. [16] proposed the module-based SOC estimation algorithm to estimate the cell SOC evolution and achieved good results, but the SOC accuracy relies on the simulation of the mathematical models; Samadi et al. [17] proposed the new Kalman filter (KF) model based on Takagi Sugeno fuzzy system to estimate SOC. The KF methods have a closed-loop correction structure, which can solve the problem of initial SOC value error, and it does not need the large data set to train the battery model, so it has been widely used. For the nonlinear system, the extended KF (EKF) and unscented KF (UKF) are applied in reference [1], [18]–[24], and the estimation results show the effectiveness of the algorithms. However, EKF uses the Taylor formula to expand the equation but ignores the higher-order term, which will lead to the inaccuracy of SOC estimation. UKF transforms the approximate linear function to the probability density function by using the unscented transformation (UT), the results show that UKF is more accurate and easier to implement than EKF. However, the noise covariance in UKF is set by human experience, which may lead to the divergence of filtering results. Therefore, the adaptive UKF algorithm is used to adjust the noise covariance of the system and improve the accurate estimation of state variables.

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Although some work has been done in lithium-ion battery modeling and SOC estimation, the electrochemical model and ECM depend on the internal parameters of the battery that cannot be ignored. Therefore, in order to reduce the dependence on the internal parameters of the battery and obtain better results, in this article, a new battery model based on the AUKF is created. The core contributions are as follows: (1) Based on the LSSVM theory, SOC and current are used as inputs of LSSVM to realize the voltage estimation. (2) A novel framework based on LSSVM is proposed to improve the accuracy of voltage. (3) The new state-space equations of AUKF is proposed. The LSSVM is used as the measurement equation of the AUKF, and joint modeling based on AUKF and LSSVM is created to estimate SOC. (4) The feasibility and stability of the proposed method were verified under different conditions. (5) Through comparison with the results of traditional LSSVM, the improved LSSVM can promote voltage estimation accuracy and reduce the calculation time. (6) Compared with Reference [36], the experimental results show that the model can improve the estimation accuracy of SOC, which reveals the feasibility and superiority of the proposed model.

The remaining sections are organized as follows: Section II introduces the terminal voltage estimation based on the LSSVM. Section III describes the SOC estimation method based on AUKF. Experimental verification in Section IV. Finally, the conclusions for the proposed model in this article are shown in Section V.

II. TERMINAL VOLTAGE ESTIMATION BASED ON LSSVM

LSSVM is an improved SVM algorithm. By constructing the loss function, the quadratic optimization of SVM is transformed into solving the linear equation [31]. Assume the training sample is \( \{x_i, f(x_i)\}_{i=1}^{n} \), \( x_i \) is the input vector, and \( f(x_i) \) is the corresponding value. The regression model of LSSVM expression is as follows:

\[
f(x_i) = \omega \psi(x_i) + b
\]

where \( \psi(\cdot) \) is the kernel function, \( \omega \) is the weight vector, and \( b \) is the deviation value.

To determine the optimal parameters (\( \omega, b \)) of (1), LSSVM uses the structural risk principle and chooses the quadratic of the error \( e_i \) as the loss function. Its optimization problem is as follows:

\[
\min J(\omega, e) = \frac{1}{2} \omega^T \omega + \frac{1}{2} C \sum_{i=1}^{n} e_i^2
\]

\[
\text{s.t. } f(x_i) = \omega^T \psi(x_i) + b + e_i
\]

The Lagrange method is introduced to transform (2) into a quadratic programming problem:

\[
L(\omega, b, e, \alpha) = J(\omega, e) - \sum_{i=1}^{n} \alpha_i (\omega^T \psi(x_i) + b + e_i - f(x_i))
\]

where \( \alpha_i \) is the \( i \)th Lagrangian operator, \( C \) is a penalty factor, and the optimal \( \alpha_i \) and \( b \) can be obtained by the KKT
FIGURE 1. LSSVM: terminal voltage estimated based on LSSVM.

condition:

\[
\begin{align*}
\frac{\partial L}{\partial \omega} &= 0 \\
\frac{\partial L}{\partial b} &= 0 \\
\frac{\partial L}{\partial \alpha_i} &= 0 \\
\frac{\partial L}{\partial e_i} &= 0
\end{align*}
\]

If \( k(x_i, x_j) \) satisfies Mercer’s condition, then (3) and (4) are combined to get the equations:

\[
f(x_i) = \sum_{i=1}^{\infty} \alpha_i k(x, x_i) + b
\]

The radial basis function (RBF) has a strong anti-interference ability for the noise in the data. This article chooses the RBF as the kernel function:

\[
k(x_i, x_j) = e^{\frac{-|x_i - x_j|^2}{2 \sigma^2}}
\]

Therefore, the current and SOC are taken as the input vectors of the LSSVM. The terminal voltage estimated based on LSSVM is shown in Figure 1.

The Figure1 shows the LSSVM model at sampling time \( k \). The SOC (\( k \)) and current \( i(k) \) of LIBs measured at time \( k \) are used as the input vectors of LSSVM, \( V(k) \) are the corresponding voltage values. Due to the non-linear relationship between the internal parameters of the LIBs, the LSSVM is selected to establish the relationship between SOC, voltage, and current. According to Eq.(5), the estimated equation of \( V(k) \) is:

\[
V(k) = \sum_{k=1}^{\infty} \sum_{i=1}^{\infty} a_i \cdot k(SOC_k, i_k) + b
\]

The LSSVM model has two important parameters to identify: penalty factor \( C \) and kernel parameter \( \sigma \). To obtain the optimal parameters (\( C, \sigma \)), a cross-validation method is applied. In this article, the experimental data \( D(X, y) \) were collected where the battery was tested under different working conditions. The \( X \) represents the measured SOC and current, and the \( y \) represents the voltage \( V \). Firstly, the data are normalized, and then the model is trained by a 10-fold cross-validation method to obtain the optimal parameters of the LSSVM. The specific steps are shown in TABLE 1.

### III. SOC ESTIMATION BASED ON AUKF METHOD

#### A. SOC ESTIMATION BASED ON AUKF METHOD

The SOC is the ratio of residual capacity to rated capacity under certain discharging conditions:

\[
SOC = SOC_0 - \frac{\int_0^t \eta i(\theta) d\theta}{Q_0}
\]

Among them, \( Q_0 \) is the rated capacity of the LIBs; \( i(\theta) \) is the current at the \( \theta \) sample time, \( \eta \) is the discharging and charging efficiency, \( SOC_0 \) is the initial value.

The discretization of Eq. (8) can be used as the state equation in the KF, where \( x_k \) represents the SOC at the sampling \( k \) time.

\[
x_{k+1} = x_k - \frac{\eta}{Q_0} \Delta t \cdot i_k
\]

At present, a variety of battery models are used in the literature. Xiong et al. [32] proposed an EKF based on multiple-time scales to realize the joint estimation of parameters and SOC of LIBs. He et al. [33] used the unscented Kalman filter (UKF) to estimate SOC, and the root mean square error (RMSE) of SOC estimation was less than 5%. Wei et al. [34] and Li et al. [35] used adaptive UKF to estimate ohmic internal resistance in the power battery model in real-time and the RMSE was controlled within 2%. Different from these methods, a SOC estimation framework based on AUKF is presented, the LSSVM is used as a measurement equation [36]. The Eq.(8) and Eq. (6) are taken as the state equation and measurement equation of AUKF respectively. Because there are errors in the process of data measurement and model building, state noise and measurement noise are introduced into the Eq. (9).

\[
\begin{pmatrix}
x_k \\
y_{k-1}
\end{pmatrix}
= \begin{pmatrix}
x_k \\
V_{k-1}
\end{pmatrix}
= \begin{pmatrix}
x_{k-1} - \frac{\eta}{Q_0} \Delta t \cdot i_k \\
\sum_{k=2}^{\infty} a_i \cdot k(x_{k-1}, i_{k-1}) + b
\end{pmatrix}
+ \begin{pmatrix}
q_k \\
r_k
\end{pmatrix}
\]

where \( x_k \) is the SOC value at \( k \) time and \( y_{k-1} \) represents the estimated voltage at \( k-1 \) time, which are defined as the state vectors and measurement vectors respectively. \( q_k \) and \( r_k \) are the state noise and measurement noise, respectively.
B. SOC ESTIMATION BASED ON AUKF-IMPROVED LSSVM

As the measurement equation of AUKF, the estimation accuracy of terminal voltage \( V(k) \) will affect the estimation result of SOC(\( k \)). Due to the accuracy of data acquisition equipment or measurement errors in the acquisition process, it may reduce the accuracy of voltage estimation. Based on this, a novel terminal voltage estimation method based on improved LSSVM is proposed to improve the accuracy of voltage estimation. As shown in Figure 2, the \( i(k) \) and \( V(k) \) represents the measured current and voltage at \( k \) time. The \( V(k−1) \) is estimated at the \( k−1 \) time, which is used as a feedback vector.

As the input vectors of LSSVM, its number will affect the accuracy of voltage estimation. In the process of voltage estimation, its value will not change suddenly in the instantaneous time. Based on this, a tap delay is added to the LSSVM model, and the voltage estimated at the sample time \( k−1 \) is taken as the feedback vector of the model to make the LSSVM forms a closed-loop model. The feedback vector \( V(k−1) \) is used to adjust the inputs of the LSSVM, to improve the \( V(k) \) performance estimation accuracy. The improved LSSVM is defined as:

\[
V_k = \sum_{k=2}^{\infty} \alpha_k i(k), SOC_k, V_{k−1} + b
\]  

Hence, this article proposes a novel algorithm based on AUKF-improved LSSVM to estimate SOC, which defined as:

\[
x_k = \begin{pmatrix} x_{1,k} \\ x_{2,k−1} \end{pmatrix} = \begin{pmatrix} x_{1,k−1} - \frac{\eta}{Q_0} \Delta t \cdot i_k \\ V_{k−1} \end{pmatrix} + \begin{pmatrix} q_1(k) \\ q_2(k) \end{pmatrix}
\]

\[
y_k = \begin{pmatrix} y_{1,k} \\ y_{2,k} \end{pmatrix} = \begin{pmatrix} V_k \\ V_{k−1} \end{pmatrix} + \begin{pmatrix} r_1(k) \\ r_2(k) \end{pmatrix}
\]

where \( x_k = [x_{1,k}, x_{2,k−1}]^T \) denotes the SOC at sampling time \( k \) and voltage at \( k−1 \) time respectively, which are viewed as the state vectors; \( y_k = [y_{1,k}, y_{2,k}]^T \) represents the voltage at \( k \) and \( k−1 \) time respectively, which are treated as the measurement vectors. \( Q_k = [q_1(k), q_2(k)]^T \) and \( R_k = [r_1(k), r_2(k)]^T \) denotes state noise and measurement noise, respectively.

C. THE ESTIMATION ALGORITHM BASED ON AUKF

AUKF is extensively applied to nonlinear control applications and deal with state estimation problems, the difference between the actual value and the estimated value is used to adaptively adjust the noise covariance, which can achieve good estimation results. According to the proposed model in Section B, the state-measurement equations are discretized as follows:

\[
\begin{align*}
x_{k+1} &= f(x_k, u_k) + Q_k \\
y_k &= h(x_k, u_k) + R_k
\end{align*}
\]

where \( f(\cdot) \) and \( h(\cdot) \) are the nonlinear function, where \( x_{k+1} = [x_{1,k+1}, x_{2,k}]^T \) denotes the system state vectors, \( y_k = [y_{1,k}, y_{2,k}]^T \) denotes the measurement vectors.

\[
\begin{align*}
Q_k &= E[q_k q_k^T] \\
R_k &= E[r_k r_k^T]
\end{align*}
\]

where \( Q \) and \( R \) are covariance matrices of system noise respectively. In this article, the corresponding algorithm steps of AUKF are given.

1. Algorithm initialization: initialization \( x_0 \) and covariance \( P_0 \):

\[
x_0 = E[x_1(0), x_2(0)];
\]

\[
P_0 = E[(x_0 - \bar{x}_0)(x_0 - \bar{x}_0)^T];
\]

2. Generating sigma points:

\[
\begin{align*}
\chi_0 &= \bar{x} \\
\chi_i^e &= \bar{x} + (\sqrt{(n + \lambda)P_x})_i, \quad i = 1, \ldots, n \\
\chi_i^o &= \bar{x} - (\sqrt{(n + \lambda)P_x})_i, \quad i = n + 1, \ldots, 2n
\end{align*}
\]

At the same time, the computation of weighted coefficients are given:

\[
\begin{align*}
\omega_0^m &= \frac{\lambda}{n + \lambda} \\
\omega_0^o &= \frac{\lambda}{n + \lambda} + (1 - \alpha^2 + \beta) \\
\omega_i^m &= \frac{1}{2(n + \lambda)}, \quad i = n + 1, \ldots, 2n
\end{align*}
\]

Among them, \( \bar{x} \) and \( P_x \) represents the mean value and variance respectively. \( \lambda = \alpha^2(L + \epsilon) - L \) is a scale parameter, \( \alpha \) is the distance between sigma point and mean point, usually set between 1e-4 and 1. \( (n + \lambda)P_x \) is a semi-positive matrix; \( L \) is the window size of covariance matching. \( \beta \) is a non-negative weight coefficient.

3. First updating the sigma point and covariance:

\[
\begin{align*}
\chi^*_k|_{k-1} &= f(\chi_k|k-1) \\
\bar{x}_k|k-1 &= \sum_{i=0}^{2n} \omega_i^o \chi^*_i|k-1 \\
P_k|k-1 &= \sum_{i=0}^{2n} \omega_i^o (\chi^*_i|k-1 - \bar{x}_k|k-1) \times (\chi^*_i|k-1 - \bar{x}_k|k-1)^T + Q_{k-1}
\end{align*}
\]

4. Updating the covariance:

\[
\begin{align*}
\gamma_{i,k|k-1} &= h(\chi^*_k|k-1)
\end{align*}
\]
According to the above algorithm, the whole SOC estimation flow chart is presented in this article. The flow chart is shown in Figure 3.

\[ \tilde{y}_{k|k-1} = \sum_{i=0}^{2n} \omega_i^m y_{i,k|k-1} \]  

(24)

\[ P_{y_i y_i} = \sum_{i=0}^{2n} \omega_i^f (y_{i,k|k-1} - \tilde{y}_{k|k-1}) \times (y_{i,k|k-1} - \tilde{y}_{k|k-1})^T + R_k^{-1} \]  

(25)

\[ P_{y_i y_i} = \sum_{i=0}^{2n} \omega_i^f (y_{i,k|k-1} - \tilde{y}_{k|k-1}) \times (y_{i,k|k-1} - \tilde{y}_{k|k-1})^T \]  

(26)

\[ K_k = P_{y_i y_i} P_{y_i y_i}^{-1} \]  

(27)

\[ \bar{x}_{k|k-1} = \bar{x}_{k|k-1} + K_k (y_k - \tilde{y}_{k|k-1}) \]  

(28)

\[ P_k = P_{k|k-1} - K_k P_{y_i y_i} K_k^T \]  

(29)

\[ Q_k = K_k H_k K_k^T \]  

(30)

\[ R_k = (y_{i,k|k-1} - \tilde{y}_{k|k-1} + u_k) \times (y_{i,k|k-1} - \tilde{y}_{k|k-1} + u_k)^T + H_k \]  

(31)

where:

\[ H_k = \sum_{i=0}^{k-L+1} \mu_k H_k^T \]  

(32)

\[ \mu_k \] is expressed as:

\[ u_k = y_k - \tilde{y}_{k|k-1} \]  

(33)

**FIGURE 3.** The flowchart of the algorithm.

**TABLE 2.** The NMC battery detailed information.

| Capacity (Ah) | Quality (Kg) | Surface area (m²) | Specific heat (J/g*K) | Upper voltage (V) | Lower voltage (V) |
|---------------|--------------|-------------------|-----------------------|------------------|------------------|
| 2.4           | 0.048        | 0.0169            | 1232                  | 4.2              | 3.4              |

**IV. RESULTS AND DISCUSSIONS**

**A. TEST BENCH**

The test bench is established to record the current, voltage, dynamic cycles condition, and other information of the battery under stable environmental conditions. The structure of the test bench is shown in Figure 4, which includes the battery test system EVT500-500, a host computer, the thermal chamber, the Fluke, and several cells. The EVT500-500 is suitable for charging and discharging, the battery test is realized by the host computer. The thermal chamber provides a stable temperature environment. The Fluke can collect multiple groups of data and convert complex data into intuitive graphs and tables.

**B. SOC ESTIMATION UNDER DST CONDITIONS**

In this article, the NMC type of LIBs was used for the experiment, the specific parameters are shown in TABLE 2.

After the initial cycles, a dynamic stress test (DST) was performed, the 6,000 samples were collected at an interval of 1 second. The corresponding voltage, current, and SOC profiles are shown in Figure 5.

In addition, three types of evaluation criteria are used in this article, which include RMSE, MAE and relative error \( e_r \). Each evaluation standard is defined as follows:

\[ y_{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_{exp,i} - y_{est,i})^2} \]  

(34)

\[ e_r = \frac{y_{exp,i} - y_{est,i}}{y_{est,i}} \]  

(35)

\[ y_{MAE} = \frac{ye_{est,i} - y_{est,i}}{|y_{est,i}|} \]  

(36)

where \( y_{exp,i} \) is the actual value and \( y_{est,i} \) is the estimated value.

Before the terminal voltage estimation, the data shall be processed according to TABLE 3. As shown in Figure 6 (a), the estimated terminal voltage is closer to the actual value. From Figure 6 (b), the relative error \( e_r \) of the estimated voltage based on LSSVM varies from −0.029V to 0.023V, while
the minimum error of the estimated voltage by improved LSSVM is $-0.016V$ and the maximum error is $0.012V$, compared with LSSVM, the MAE is decreased by 44.8%. At the same time, the stability parameter RMSE of the proposed model is further reduced from 1.68% to 1.14%. Besides, the total time consumption of the LSSVM model and improved LSSVM model in voltage estimation are compared. The calculation results show that the time-consumption of the LSSVM model in voltage estimation is 6.73 seconds, and that of the improved LSSVM model is 5.68 seconds. Compared with LSSVM, the improved LSSVM reduces the time consumption by 15.6%, which indicates that the improved LSSVM can not only improve the accuracy and stability of voltage estimation, but also show that the proposed model use much less computational time.

In order to prove the robustness of the algorithms, the initial value of SOC is set to 0.6. From Figure 6(c), the convergence speed of SOC estimated by two methods is similar. In this
TABLE 3. Estimated terminal voltage and SOC under DST cycles.

| Statistical parameter | Model        | RMSE(%) | MAE(%) |
|------------------------|--------------|---------|--------|
| Terminal Voltage       | LSSVM        | 1.68    | 2.9V   |
|                        | Improved LSSVM | 1.14    | 1.6V   |
| SOC                    | AUKF-LSSVM   | 1.21    | 2.04   |
|                        | AUKF-Improved LSSVM | 0.99    | 1.48   |

The AUKF based on the improved LSSVM significantly improves the estimation accuracy of SOC. From the TABLE 3, the MAE is decreased from 2.04% to 1.48%, the estimation accuracy of SOC increased by 27.4%. In addition,
the RMSE of the estimated SOC is further reduced from 1.21% to 0.99%. Compared with AUKF-LSSVM, it also manifests that the results of the proposed model are more reliable. When SOC is lower than 20%, the MAE of the proposed model is 2.04%, and when SOC is higher than 20%, the MAE is 1.17%. The main reason for the increased error is due to the nonlinear characteristics inside the battery, so it may produce a larger SOC estimation deviation. Compared with Refs [32]–[34], the proposed method can obtain satisfactory results.

C. SOC ESTIMATION UNDER UDDS CYCLES

The proposed model is further verified under UDDS to prove its universality. The corresponding current, voltage, and SOC profiles are shown in Figure 7.

Figure 8 (a) - (d) shows the results of each estimator. From the Figure 8 (a) - Figure 8 (b), test results are very similar to DST, and the proposed model has good estimation accuracy and stability in terminal voltage estimation and SOC estimation. It can be indicated that the MAE of the predicted terminal voltage by improved LSSVM is reduced from 5.9% to 5.2%, the estimation accuracy of terminal voltage is increased by 13.5%, and the RMSE is reduced from 2.35% to 1.69%, which show that the improved LSSVM has better estimation accuracy and stability than the traditional LSSVM. Similarly, the total voltage estimation time of the improved LSSVM model is 7.66 seconds. Compare with the LSSVM, the time consumption is reduced by 20.2%, which further presents the effectiveness of the proposed method.

In addition, the initial value of SOC is set to 0.5, Figure 8(c) shows the estimated SOCs are convergent to the actual value. From Figure 8(c) - (d) and TABLE 4, it can clearly be indicated that the relative error of SOC estimated by AUKF-improved LSSVM varies from −1.24% to 1.97%, Compared with AUKF-LSSVM, the MAE and RMSE are increased by 15.4% and 6.73% respectively, which further show that the SOC and terminal voltage estimated by the proposed battery model has better estimation accuracy and stability.

V. CONCLUSION

Accurate SOC estimation is very important for EVs. To obtain better SOC estimation accuracy, joint modeling of AUKF and LSSVM is proposed to estimate SOC. The nonlinear relationship between SOC, current, and voltage can be established by the LSSVM model. Due to the estimation accuracy of terminal voltage will directly affect the estimation results of SOC. Based on this, a novel voltage estimation method based on improved LSSVM is proposed. The terminal voltage estimated at the previous time is fed back to the input vectors, together with the current and SOC at the current time are used as the input vectors of LSSVM to estimate the terminal voltage. In addition, the measurement equation of the novel AUKF is created by the improved LSSVM. The experimental results show that the proposed model has good estimation accuracy for terminal voltage and SOC. The SOC estimation error is controlled within 2%, which proves the validity and stability of the algorithm.

However, this method selects the latest battery for data collection, so in the future, it will pay more attention to the influence of battery aging and temperature on the model and reduce the calculation burden.

REFERENCES

[1] H. Aung, K. S. Low, and S. T. Goh, “State-of-Charge estimation of lithium-ion battery using square root spherical unscented Kalman filter (Sqrt-UKFST) in nanosatellite,” IEEE Trans. Power Electron., vol. 30, no. 9, pp. 4774–4783, Sep. 2015.
[2] Z. Li, J. Huang, B. Y. Liaw, and J. Zhang, “On state-of-charge determination for lithium-ion batteries,” J. Power Sources, vol. 348, pp. 281–301, Apr. 2017.
[3] H. Mu, R. Xiong, H. Zheng, Y. Chang, and Z. Chen, “A novel fractional order model based state-of-charge estimation method for lithium-ion battery,” Appl. Energy, vol. 207, pp. 384–393, Dec. 2017.
[4] X. Tang, F. Gao, C. Zou, K. Yao, W. Hu, and T. Wick, “Load-responsive model switching estimation for state of charge of lithium-ion batteries,” Appl. Energy, vol. 238, pp. 423–434, Mar. 2019.
[5] G. Wenkai, Z. Yueju, and O. Minggao, “Micro-short-circuit diagnosis for series-connected lithium-ion battery packs using mean-difference model,” IEEE Trans. Ind. Electron., vol. 66, no. 3, pp. 2132–2142, Mar. 2019.
[6] X. Tang, B. Liu, F. Gao, and Z. Lv, “State-of-Charge estimation for li-ion power batteries based on a tuning free observer,” Energies, vol. 9, no. 9, p. 675, Aug. 2016.
[7] H. Dai, T. Xu, L. Zhu, X. Wei, and Z. Sun, “Adaptive model parameter identification for large capacity li-ion batteries on separated time scales,” Appl. Energy, vol. 184, pp. 119–131, Dec. 2016.
[8] W. Wang, X. Wang, C. Xiang, C. Wei, and Y. Zhao, “Unscented Kalman filter-based battery SOC estimation and peak power prediction method for power distribution of hybrid electric vehicles,” IEEE Access, vol. 6, pp. 35957–35965, 2018.
[9] A. Hammouche, E. Karden, and R. W. De Doncker, “Monitoring state-of-charge of Ni-MH and Ni-Cd batteries using impedance spectroscopy,” J. Power Sources, vol. 127, nos. 1–2, pp. 105–111, 2004.
[10] F. Codecà, S. M. Savarese, and V. Manzoni, “The mix estimation algorithm for battery State-of-Charge estimator- Analysis of the sensitivity to measurement errors,” in Proc. 48th IEEE Conf. Decis. Control (CDC) Held Jointly 25th Chin. Control Conf., Dec. 2009, vol. 79, no. 7, pp. 8083–8088.
[11] F. Sun, R. Xiong, and H. He, “A systematic state-of-charge estimation framework for multi-cell battery pack in electric vehicles using bias correction technique,” Appl. Energy, vol. 162, pp. 1399–1409, 2016.
[12] K. A. Smith, C. D. Rahn, and C. Y. Wang, “Model-based electrochemical estimation of lithium-ion batteries,” in Proc. IEEE Int. Conf. Control Appl., Sep. 2008, pp. 714–719.
[13] W. Fang, O. J. Kwon, and C. Wang, “Electrochemical–thermal modeling of automotive Li-ion batteries and experimental validation using a three-electrode cell,” Int. J. Energy Res., vol. 34, no. 2, pp. 107–115, 2010.
[14] F. Sun, X. Hu, Y. Zou, and S. Li, “Adaptive unscented Kalman filtering for state of charge estimation of a lithium-ion battery for electric vehicles,” Energy, vol. 36, no. 5, pp. 3531–3540, 2011.
[15] W. Han, L. Zhang, and Y. Han, “Computationally efficient methods for state of charge approximation and performance measure calculation in series-connected battery equalization systems,” J. Power Sources, vol. 286, pp. 145–158, Jul. 2015.
Z. Yongfei, W. Huaixing, H. Fang, Y. Xin, and Z. Jing, “Estimation of cell SOC evolution and system performance in module-based battery charge equalization systems,” *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 4717–4728, Sep. 2019.

M. F. Samadi and M. Saifi, “State-space modeling and observer design of Li-ion batteries using Takagi-Sugeno fuzzy system,” *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 1, pp. 301–308, Jan. 2017.

F. Claude, M. Becherif, and H. S. Ramadan, “Experimental validation for Li-ion battery modeling using extended Kalman filters,” *Int. J. Hydrogen Energy*, vol. 42, no. 40, pp. 25509–25517, Oct. 2017.

K. S. R. Mawonou, A. Eddahech, D. Dumur, D. Beauvois, and E. Godoy, “Experimental validation for Li-ion battery modeling using extended Kalman filters,” *J. Power Sources*, vol. 383, pp. 50–58, Apr. 2018.

W. Zhang, W. Shi, and Z. Ma, “Adaptive unscented Kalman filter based state of energy and power capability estimation approach for lithium-ion battery,” *J. Power Sources*, vol. 289, pp. 50–62, Sep. 2015.

M. S. El Din, A. A. Hussein, and M. F. Abdel-Hafez, “Improved battery SOC estimation accuracy using a modified UKF with an adaptive cell model under real EV operating conditions,” *IEEE Trans. Transp. Electrific.*, vol. 4, no. 2, pp. 445–452, Jun. 2018.

C. Huang, Z. Wang, Z. Zhao, L. Wang, C. S. Lai, and D. Wang, “Robustness evaluation of extended and unscented Kalman filter for battery state of charge estimation,” *IEEE Access*, vol. 6, pp. 27617–27628, 2018.

W. He, N. Williard, C. Chen, and M. Pecht, “State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation,” *Int. J. Electro Power Energy Syst.*, vol. 62, pp. 783–791, Nov. 2014.

L. Kang, X. Zhao, and J. Ma, “A new neural network model for the state-of-charge estimation in the battery degradation process,” *Appl. Energy*, vol. 121, pp. 20–27, May 2014.

H. Chaoui and C. C. Ibe-Ekoocha, “State of charge and state of health estimation for lithium batteries using recurrent neural networks,” *IEEE Trans. Veh. Technol.*, vol. 66, no. 10, pp. 8773–8783, Oct. 2017.

J. N. Hu, J. J. Hu, and H. B. Lin, “State-of-charge estimation for battery management system using optimized support vector machine for regression,” *J. Power Sources*, vol. 269, pp. 682–693, Dec. 2014.

H. Sheng and J. Xiao, “Electric vehicle state of charge estimation: Non-linear correlation and fuzzy support vector machine,” *J. Power Sources*, vol. 281, pp. 131–137, May 2015.

J. C. A. Anton, P. J. G. Nieto, C. B. Viejo, J. A. V. Vilán, “Support vector machines used to estimate the battery state of charge,” *IEEE Trans. Power Electron.*, vol. 28, no. 12, p. 5919–5926, Dec. 2013.

Z. Yongfei, W. Huaixing, H. Fang, Y. Xin, and Z. Jing, “SOC estimation of power battery based on LSTM neural network,” *Comput. Appl. Softw.*, vol. 37, no. 3, pp. 78–81 and 88, 2020.

R. Xiong, F. Sun, Z. Chen, and H. He, “A data-driven multi-scale extended Kalman filtering based parameter and state estimation approach of lithium-ion polymer battery in electric vehicles,” *Appl. Energy*, vol. 113, no. 1, pp. 463–476, 2014.

W. He, N. Williard, C. Chen, and M. Pecht, “State of charge estimation for electric vehicle batteries using unscented Kalman filtering,” *Microelectron. Rel.*, vol. 53, no. 6, pp. 840–847, 2013.

K. Wei and Q. Chen, “State estimation of Li-ion power battery based on adaptive traceless Kalman filter algorithm,” *Chin. J. Elect. Eng.*, vol. 3, pp. 445–452, 2014.

X. Li and S. Yu, “State of charge estimation of lithium-ion battery based on novel AUKF,” *Comput. Simul.*, vol. 36, no. 9, pp. 120–125, 2019.

J. Meng, G. Luo, and F. Gao, “Lithium polymer battery State-of-Charge estimation based on adaptive unscented Kalman filter and support vector machine,” *IEEE Trans. Power Electron.*, vol. 31, no. 3, pp. 2226–2238, Mar. 2016.