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A Novel Variable Forgetting Factor Recursive Least Square Algorithm to Improve the Anti-Interference Ability of Battery Model Parameters Identification

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ABSTRACT Recursive least square (RLS) algorithms are considered as a kind of accurate parameter identification method for lithium-ion batteries. However, traditional RLS algorithms usually employ a fixed forgetting factor, which does not have adequate robustness when the algorithm has interfered. In order to solve this problem, a novel variable forgetting factor method is put forward in this paper. Comparing with traditional variable forgetting factor methods, it has higher stability and sensitivity by using some mathematic improvements. The improvements in the robustness of recursive least square with a variable forgetting factor (VFF-RLS) algorithm is verified in this paper. A Thevenin model which is frequently-used in battery management system is employed in the verification. A data loss battery working condition is designed to simulate the interference to the algorithm. A simulation platform is established in MATLAB/Simulink software, and the data used in the verification is obtained by battery experiments. The analysis indicated that the novel VFF-RLS algorithm has better robustness and convergence ability, and has an acceptable identification accuracy.

INDEX TERMS Lithium battery, variable forgetting factor, recursive least square, parameter identification, robustness.

I. INTRODUCTION

With the increasingly global environment problems and energy crisis, people is trying to find more sustainable clean energies to replace now used fossil fuels. The electricity is considered as a feasible option. Electric vehicles (EVs) are becoming more and more popular all over the world based on electricity. As the core energy storage component in the EVs, Lithium-ion batteries' performance has made great progresses in the past few decades. But battery management is still needed to keep batteries cells, as well as battery package, working in safe conditions, high efficiency, and best performance to meet the miles demands of the vehicles. State of Charge (SOC), as a crucial parameter in battery management, illustrates the electricity energy left in battery. However, different from the traditional inner combustion vehicles, the battery SOC cannot be measured directly in EVs. It can only be estimated by using several terminal parameters of the battery, such as current, voltage, temperature, etc. High accurate SOC estimation algorithm has received a huge amount of attention because of its importance and difficulties [1].

The SOC estimation procedure can be divided into three steps: battery modeling, parameter identification and SOC estimation. In order to improve the estimation accuracy and convergence online, an appropriate battery model with high accuracy and simple structure is inevitable. Nowadays, the equivalent circuit models of lithium battery are the most commonly used in the studies of online SOC estimation [2], [3]. Battery behaviors are represented by an equivalent circuit, including an equilibrium voltage source, an internal resistance and at least one RC pair which are connected in series [4]. The RC pairs are used to represent the electrochemical polarization dynamics in the battery. The higher the RC pairs order is, the more complex the model is. Because

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the number of model parameters, such as resistances and capacitances, are not too much, the equivalent circuit models have their unique advantages in simplicity and robustness. Thevenin model and DP model are used in equivalent circuit models mostly [5], [6]. However, this kind of models cannot predict the degradation of the battery. The parameters in the model need to be regularly updated.

The performance of the SOC estimation is affected greatly by the accuracy of the battery model's parameter identification. These parameter values are not always constant. They will be changed in different working situations such as battery charging/discharging, battery aging, and working temperature. In traditional method on parameter identification, it is needed to obtain the parameter table in different SOC and temperature. This kind of methods are mostly realized by using the Least Square (LS) algorithm. The LS algorithm has many advantages such as high accuracy, no calculation speed limit and easy designed. However, the disadvantages of this method are also very obvious. Firstly, all the identified parameters need to be stored in the Battery Management System (BMS), and it will take up a lot of storage space. Secondly, after the battery works for a period of time, the parameters in the battery model will be changed. It will lead to big error in SOC estimation. Therefore, in recent years, an on-line parameter identification method has started to be developed [7]. In 2012, a method of on-line parameter identification which based on RLS algorithms was put forward by He and Xiong [8]. This method has been widely concerned, and used in academic studies. For example, Wei *et al.* [9] applied this RLS method to a vanadium redox flow battery model whose OCV parameter is decoupled from RLS observer to reduce the possibility of cross interference and the number of RLS parameter.

Serval variant RLS algorithms, which are not focus on forgetting factor, were used in parameter identification. In [10], a decoupled weighted RLS was developed to identify Lithium battery model's fast dynamic parameters and slow dynamic parameters that response in different time scale. However, this algorithm considers the fast dynamic parameters and slow dynamic parameters as constant during different working condition and require to offline training, without high adaptive ability. Another variant RLS in [11] enhance the robustness of RLS in battery impedance estimation by set dead-zone to the covariance matrix of RLS to prevent its wind-up problem, but this dead-zone limits the adaptive ability of RLS at large error conditions. Unlike this decoupled weighted RLS, Dai *et al*. [12] proposed a method to estimate the slow dynamic battery parameters by coupling an extended Kalman filter, which relies on of estimation of SOC result from BMS system.

In RLS algorithm, the forgetting factor is a very important parameter. Its value will affect the convergence rate of the algorithm and the sensitivity to noise. In traditional studies, the forgetting factor was always obtained by trial and error method or Newton's method [10], and was used as a constant in the algorithm. A well-known self-tuning method for exponentially varying forgetting factor is derived by Fortescue *et al.* for control system in chemical plants [13]. However, Kim *et al.* addressed that Fortescue' forgetting factor and its variants cannot solve the wind-up problem of covariance matrix in RLS of battery parameter identification [14], where variable forgetting factors are constrained within a small region near one, instead of previous exponential varying range from 0 to 1, which may heavily limit the adaptive ability of RLS. A variants of Fortescue's variable forgetting factors regulator also adopted by Duong *et al*., to a vector type RLS with multiple adaptive forgetting factors and achieved accurate identified results for LiFePO4 battery's ECM model parameters [15], while how to tune the sensitiveness of multiple forgetting factors is not mentioned, which is more difficult than single forgetting factors. Moreover, the RLS parameters decoupling ability of this vector type RLS may not as satisfying as assumed, because the decoupled parameters are coupled during both the update gain vector calculation in vector type RLS and reversed solution from RLS parameters to battery's equivalent circuit model parameters. These multiple forgetting factors were optimized by Rozaqi *et al.* [16], which also conducted comparison between the optimized performance by particle swarm optimization, single objective genetic algorithm and multiple objective genetic algorithm. However, this optimization by evolution algorithms are developed for fixed forgetting factors, instead of optimizing variable adaptive forgetting factors for more working conditions that required more training with more data.

In 2016, an improved battery on-line parameter identification method was put forward by Li *et al.* [17]. In his research, the astringency and reliability of the RLS algorithm are proved. The importance of the forgetting factor also be mentioned in the paper. Zhirun Li pointed out that the sample time would affect the optimal value of the forgetting factor. In [19], in order to improve the stability of the algorithm, a certain number (window) of past data points are used to identify the parameters. In [20], RLS algorithm is used to the estimate open circuit voltage (OCV) of lithium batteries that has strong relationship with SOC.

In this paper, a new method to obtain the forgetting factor which is named VFF-RLS algorithm is put forward. The forgetting factor in this method is determined by the prediction error, and is changed adaptively with the processing of the algorithm. This method can improve the parameter identification's convergence rate when the signals fluctuate violently or when the signals change drastically. The method can also ensure a high identification accuracy when the signals are stable. In reference [21], a variable forgetting factor method is put forward to improve the robustness of system identification.

II. BATTERY EXPERIMENTS

In order to obtain the basic parameters of the battery, such as capacity and SOC-OCV relationship, some battery experiments are carried out. The experiments include four tests:

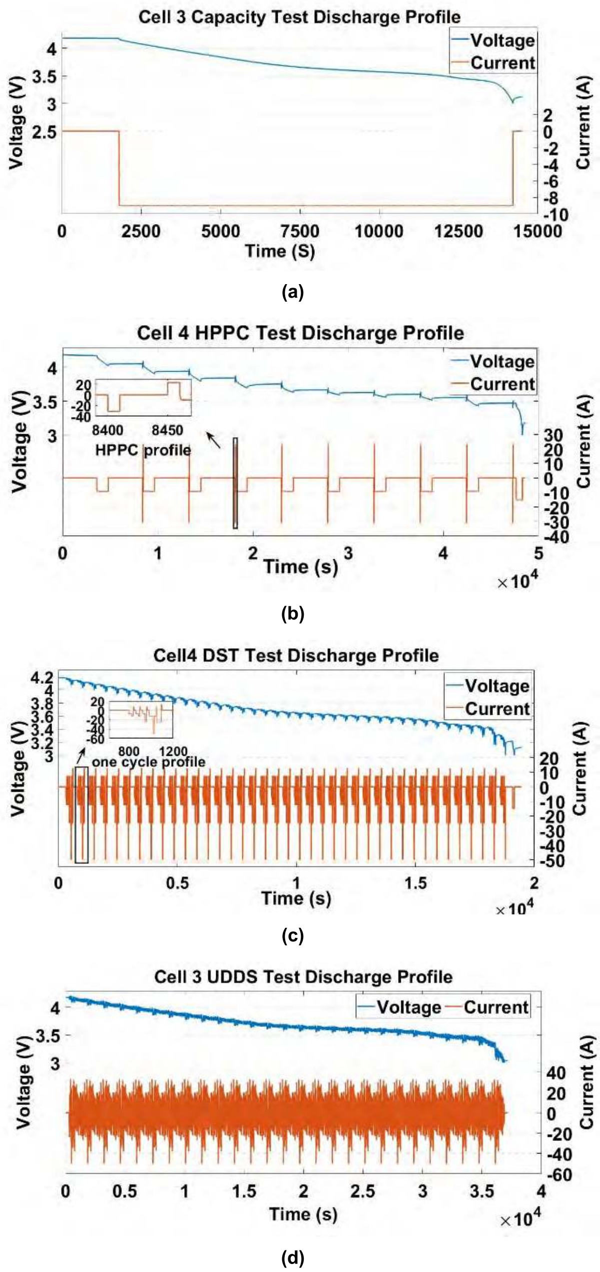

FIGURE 1. Profiles of battery experiments. (a) Capacity Test Profile. (b) HPPC test profile. (c) DST test profile. (d) UDDS test profile.

Capacity test, HPPC test, DST test [22], and UDDS test. The obtained profiles of these tests are shown in Fig. 1.

The experiments are carried out on a battery test bench which is shown in Fig. 2. The batteries are installed in an environment chamber to maintain a stable working condition. The charging and discharging operation are controlled by the battery tester Digatron MCT 50-05-8 ME with a 0.1% accuracy on current and voltage sensors. The programs of the battery tests are designed on the host computer. A paperless recorder which has temperature sensors is employed in this experiment. The sensors can detect the temperatures on

TABLE 1. Experimental battery specifications.

Battery Photo	Technical Specification
	•Nominal voltage: 3.7 V •Nominal capacity: 30 Ah •Limited charge voltage: 4.2 V •Limited discharge voltage: 3 V •Maximum charge current: 30 A •Maximum discharge current: 90 A (3 C) •Work temperature range: -20℃ to +60℃ •Size: 108mm × 150 mm × 22 mm •Weight: 700 g •Number of the samples: 6

the surface of the batteries in real-time. All the test data is returned to the host computer and stored for further analysis.

According to the Capacity test, the actual capacities of the batteries are obtained. They are shown as follows:

TABLE 2. Capacities of the battery samples.

Cell 1 30.459 Ah	Cell 2 31.037 Ah	Cell 3 31.038 Ah
Cell 4 31.088 Ah	Cell 5 31.062 Ah	Cell 5 31.008 Ah

The SOC and OCV of Lithium-ion batteries have a very strong relationship. The OCV values every 10% SOC discharging points are obtained from the HPPC test. Since this SOC-OCV relationship is only used to obtain a benchmark for algorithm reference, a polynomial least square curve fitting is adopted and calculated by MATLAB offline. For real embedded application, piece-wise linear fitting or look-up table can be used to substitute this high order polynomial curve fitting SOC-OCV relationship. The SOC-OCV relationship is described as (1):

$$\begin{aligned} U_{OC} &= f(SOC) \\ &= b_1 SOC^6 + b_2 SOC^5 + b_3 SOC^4 + b_4 SOC^3 \\ &\quad + b_5 SOC^2 + b_6 SOC + b_7 \end{aligned} \tag{1}$$

By using LS algorithm, the parameters of $b_i(i = 1, 2, \cdots 7)$ could be solved. The SOC-OCV relationship of the batteries is shown in Fig. 3.

The DST and UDDS test are used to verify the algorithms of parameter identification. The actual OCV values in these tests are seen as references in algorithm verification. The obtaining process of the actual OCV values is introduced as follows.

Step 1: Obtaining the actual capacities of the battery, which are shown in Table 2.

Step 2: Computing the actual SOC values in these tests. The method is shown in (2):

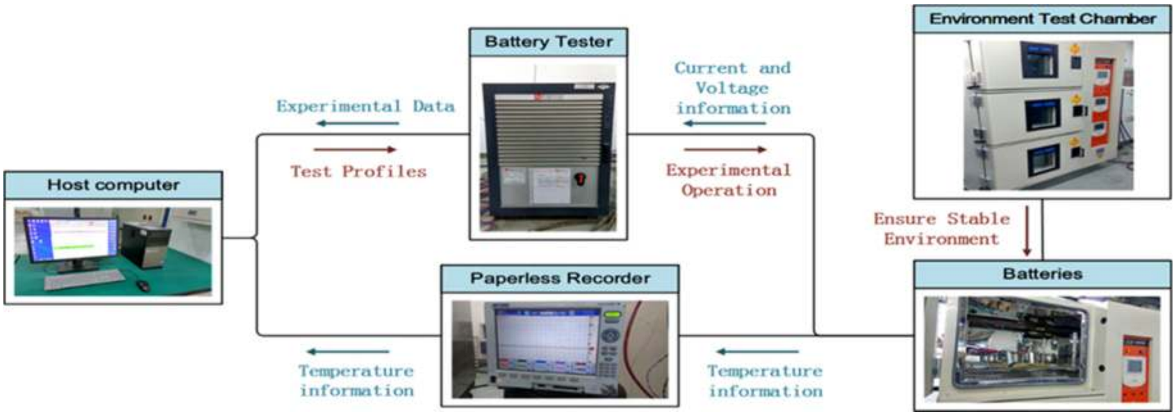

FIGURE 2. Battery experiment bench.

$$SOC_{Ref}(k) = \frac{(C_{Cap} \times SOC_{Initial} + C_{Accu}(k))}{C_{Cap}} \tag{2}$$

where, $SOC_{Ref}(k)$ is the actual SOC value; C_{Cap} is the actual capacity of the battery, $C_{Accu}(k)$ is the accumulated charge in the test, and is recorded by the battery tester.

Step 3: According to the SOC-OCV relationship shown in (1), obtaining the actual OCV values.

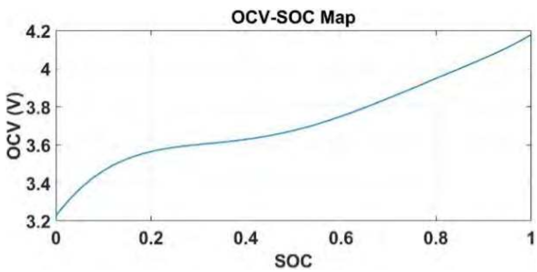

FIGURE 3. SOC-OCV relationship.

III. BATTERY MODELING

Thevenin models are widely used in recent SOC estimation studies [23]–[25]. The polarization phenomenon of Lithium batteries can be characterized by this model with simple model structure shown in Fig. 4. There are only 4 parameters in this model: the internal resistance, the polarization resistance, the polarization capacity, and the OCV value. The terminal voltage and the battery current are regarded as observed value.

According to the equivalent circuit, the relationship between the parameters and observed values can be expressed as (3):

$$U_L(s) = U_{OC}(s) - I_L(s)\left(R_0 + \frac{R_1}{1 + R_1C_1s}\right) \tag{3}$$

where, s is the frequency operator. Then, the transfer function of this system is shown as (4):

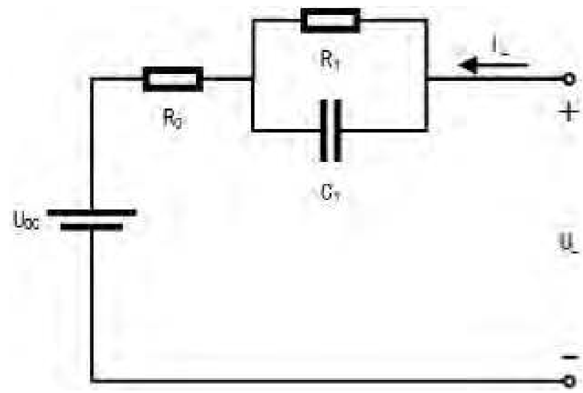

FIGURE 4. Thevenin model.

$$\begin{aligned} G(s) &= \frac{U_L(s) - U_{OC}(s)}{I(s)} = -R_0 - \frac{R_1}{1 + R_1C_1s} \\ &= -\frac{R_0 + R_1 + R_0R_1C_1s}{1 + R_1C_1s} \end{aligned} \tag{4}$$

By employing a bilinear transformation which is shown in (5), the function in (4) can be discretized as (6).

$$s = \frac{2}{T}\frac{1 - z^{-1}}{1 + z^{-1}} \tag{5}$$

where, z is the discretization operator.

$$G(z^{-1}) = -\frac{\left(\begin{array}{c}\frac{R_0T + R_1T + 2R_0R_1C_1}{T + 2R_1C_1} \\ + \frac{R_0T + R_1T - 2R_0R_1C_1}{T + 2R_1C_1} z^{-1}\end{array}\right)}{1 + \frac{T - 2R_1C_1}{T + 2R_1C_1} z^{-1}} \tag{6}$$

Define:

$$\begin{aligned} a_1 &= -\frac{T - 2R_1C_1}{T + 2R_1C_1} \\ a_2 &= -\frac{R_0T + R_1T + 2R_0R_1C_1}{T + 2R_1C_1} \end{aligned}$$

$$a_3 = -\frac{R_0T + R_1T - 2R_0R_1C_1}{T + 2R_1C_1}$$

Then, the identified parameters of R_0, R_1 and C_1 are changed to be a_1, a_2 and a_3.

The (6) can be rewritten as (7).

$$G(z^{-1}) = \frac{a_2 + a_3z^{-1}}{1 - a_1z^{-1}} \tag{7}$$

The (3) after discretization is written as (8):

$$U_L(k) - U_{OC}(k) = a_1 (U_L(k-1) - U_{OC}(k-1)) + a_2I_L(k) + a_3I_L(k-1) \tag{8}$$

where, $k = 1, 2, 3 \ldots$. Define $y_k = U_L(k)$. The (8) is rewritten as (9):

$$y_k = U_{OC}(k) + a_1 (U_L(k-1) - U_{OC}(k-1)) + a_2I_L(k) + a_3I_L(k-1) \tag{9}$$

The mathematic recursive function of the battery model is shown in (10):

$$\begin{cases} \varphi_1(k) = [1 \;\; U_L(k-1) - U_{OC}(k-1) \;\; I_L(k) \;\; I_L(k-1)] \\ \theta_1(k) = [U_{OC}(k) \;\; a_1 \;\; a_2 \;\; a_3]^T \\ y_k = \varphi_1(k)\theta_1(k) \end{cases} \tag{10}$$

The parameters that need to be used in SOC estimation are R_0, R_1, and C_1. However, the parameters identified by RLS algorithms are $U_{OC}(k)$, a_1, a_2, and a_3. Thus R_0, R_1, and C_1 need to be solved by a_1, a_2, and a_3, and the equations are shown as follows:

$$\begin{aligned} R_0 &= \frac{a_3 - a_2}{a_1 - 1} \\ R_1 &= \frac{2(a_1a_2 - a_3)}{a_1^2 - 1} \\ C_1 &= \frac{T(a_1^2 - 2a_1 + 1)}{4(a_3 - a_1a_2)} \end{aligned} \tag{11}$$

IV. PARAMETER IDENTIFICATION

A. RLS ALGORITHM

The RLS algorithm has been widely used in many studies. The core equations are listed in (12).

$$\begin{cases} y_k = \varphi_1(k)\theta_1(k) + e(k) \\ e(k) = U_L(k) - \varphi_1(k)\hat{\theta}_1(k-1) \\ K(k) = \dfrac{P(k-1)\varphi_1^T(k)}{\lambda + (k)P(k-1)\varphi_1^T(k)} \\ P(k) = \dfrac{P(k-1) - K(k)\varphi_1(k)P(k-1)}{\lambda} \\ \hat{\theta}_1(k) = \hat{\theta}_1(k-1) + K(k)e(k) \end{cases} \tag{12}$$

where, $e(k)$ is the prediction error of the U_L, $\hat{\theta}_1(k)$ is the estimated parameter vector, $K(k)$ is the algorithm gain vector, $P(k)$ is the covariance matrix, and λ, as a constant here, is the forgetting factor.

B. VFF-RLS ALGORITHM

The forgetting factor is very significant for obtaining a desirable result in parameter identification. When $\lambda = 1$, the forgetting function is not employed in the algorithm. The identification result is impacted by all the errors of the past data. The RLS algorithm is as same as LS algorithm in this case. When $\lambda = 0$, the identification result is only affected by the current data error.

Here, a modified RLS algorithm which has a variable forgetting factor (VFF-RLS) is put forward. In 1991, a variable forgetting factor method is put forward by J.D. Park [18]. In his paper, the forgetting factor of RLS algorithms could be optimized according to the prediction error at the present data point. The equations of this method are shown as follows:

$$\lambda(k) = \lambda_{\min} + (1 - \lambda_{\min}) \cdot 2^{L(k)} \tag{13}$$
$$L(k) = -\mathrm{NINT}(\rho e(k)^2) \tag{14}$$

where, NINT(x) is a function that makes x to the nearest integer, ρ is a sensitivity gain. $\lambda_{\min}$ is the minimum value of the forgetting factor. In this method, the forgetting factor would fluctuate between 1 and $\lambda_{\min}$, Which is affected by the prediction errors $e(k)$. If $e(k)$ is infinity or a very large value, the $\lambda_{\min}$ will be obtained. When the $e(k)$ is close to zero, the λ will be close to 1 (the maximum value). λ would change in an exponential rate and this rate is determined by ρ. However, the battery parameter identification by using this method cannot obtain a good result. Thus, J.D. Park's method need to be improved.

Firstly, the function NINT(x) is employed to reduce the calculation burden. However, it would lead to a serious problem that the sensitivity of the algorithm is very low. For instance, as long as the $\rho e(k)^2$ is smaller than 0.5, the $L(k)$ would be zero, which often occurs in battery model parameter identification. In this case, the λ would always be its maximum value, which is hard to obtain good parameter identification results. Thus, the effects of removing this function from the algorithm on the calculation complexity is analyzed. It can be seen from (13) that the $L(k)$ is the exponential part of the operation. The computational differences between fractional-exponential and integer-exponential arithmetic in computers are the object of concern here. The method of exponential operation in computers is as follows:

$$x^a = e^{(a \ln x)} \tag{15}$$

In this method, whether a is an integer or a fraction number, it would only affect the complexity of a multiplication step, and the influence on the global complexity of the exponential operation is little. Thus, removing NINT(x) would not lead to much extra calculation burden on the algorithm.

Secondly, J.D. Park's method only limits the minimum value of the forgetting factor. Whether 1 is an appropriate value of the maximum forgetting factor needs to be discussed. In Fig. 5, the parameter identification results in UDDS test are illustrated. The algorithms used here are RLS algorithm with different fixed forgetting factors.

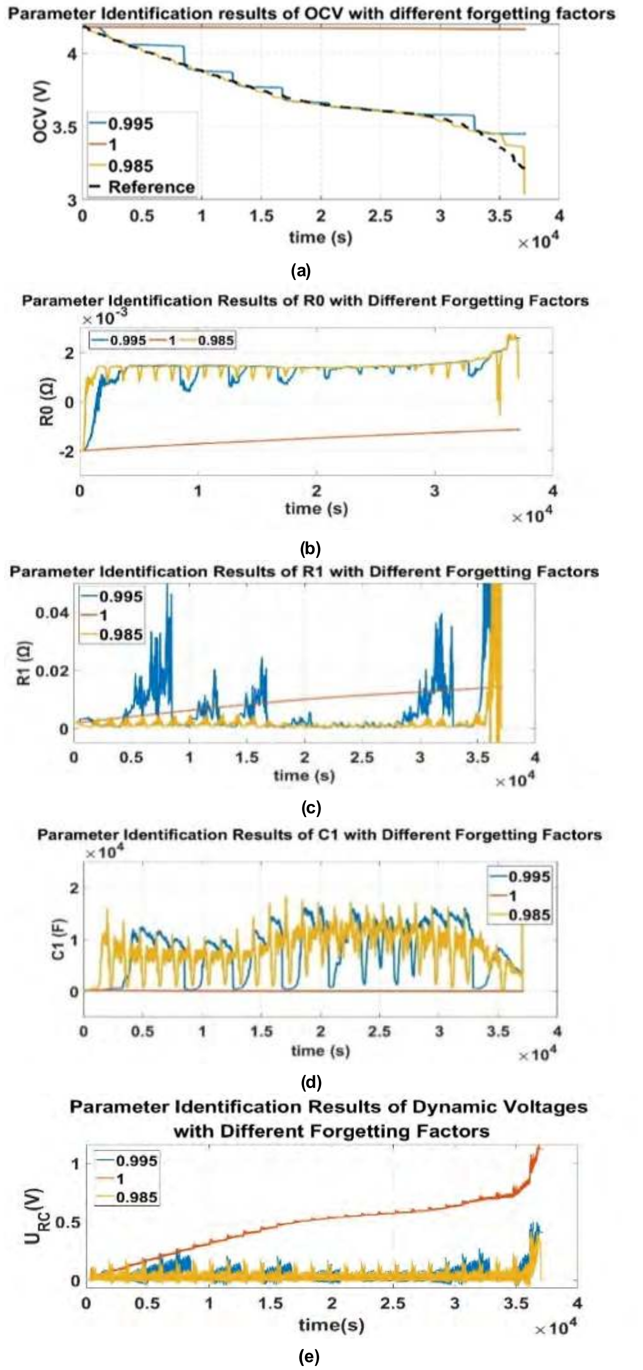

FIGURE 5. Parameter identification results with different forgetting factors. (a) OCV identification results. (b) R_0 identification results. (c) R_1 identification results. (d) C_1 identification results. (e) identification results of dynamic voltage of R-C network.

Fig. 5 respectively show the parameter identification results of U_{OC}, R_0, R_1, and C_1. The lines in blue, red, and yellow color are respectively represent the parameter identification results of RLS algorithm with 0.995, 1, and 0.985 forgetting factor. It can be seen from the figures that when the forgetting factor equals to 1, the identification results cannot follow the changes of the parameters. It cannot competent in the parameter identification of the lithium-ion battery models. Thus, in this paper the maximum value in the variable forgetting factor is replaced by another value $\lambda_{\max}$. In battery model parameter identification, $e(k)$ would be affected by battery working conditions. When the signals of current and voltage are stable, the prediction errors of the algorithm would be relatively small. Contrarily, when the signal changes dramatically, $e(k)$ would be a large value. UDDS test is a very dynamic battery working condition, and the forgetting factor under this test should be a small value. This is the reason that the RLS algorithm with a 0.985 forgetting factor has the best parameter identification results among these algorithms. Comparing with the parameter identification results of the RLS algorithm with 0.985 forgetting factor, the parameter identification results of the RLS algorithm with 0.995 forgetting factor could only partly keep up with the changes of parameters, and the accuracy is not satisfactory in this battery working condition. However, in order to meet the demand for large forgetting factor values under steady battery working conditions, the maximum value of the forgetting factor in this paper is selected as 0.995 that has good identification performance in stable battery working conditions.

Additionally, the stability of J.D. Park's method is not high. This is because that the forgetting factor is determined by only one data point, but the battery working condition need some time to be reflected. In order to solve this shortcoming, a data window theory is employed in this paper. In this method, the originally single value is replaced by the mean square of all the data in a window that moves over time. It could reduce the disturbance of individual data points and increase the stability of the algorithm

Therefore, the novel variable forgetting factor method is shown as follows:

$$L(k) = -\rho \frac{\sum_{i=k-M+1}^{k} e_i e_i^T}{M} \tag{16}$$

$$\lambda(k) = \lambda_{\min} + (\lambda_{\max} - \lambda_{\min}) \cdot 2^{L(k)} \tag{17}$$

where, M is the range of the window.

In this method, the NINT(x) function is removed. The maximum value of the forgetting factor is replaced from 1 to $\lambda_{\max}$. The $\lambda(k)$ is determined by the mean square value of M prediction errors. Therefore, the VFF-RLS algorithm is put forward. This algorithm can quickly be converged when the signal fluctuation is violent, and will keep a high estimation accuracy when the signal is stable. In this paper, an analysis of convergence and robustness of this algorithm is done below.

V. SIMULATION ANALYSIS

Robustness is the ability of resisting the disturbance of signals. In order to simulate the situations that the BMS is

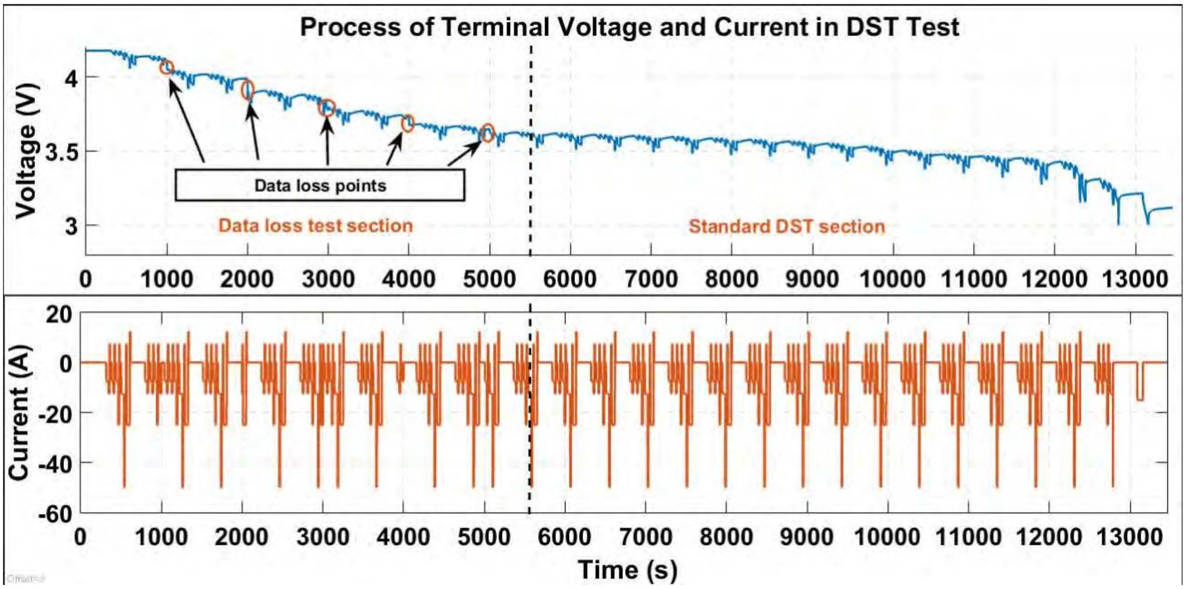

FIGURE 6. Data loss working condition test profile.

failed or the data from sensors is not accurate, a ''data loss'' working condition is designed in this paper. This test is modified from the DST test, and the profile of U_L and I_L is shown in Fig. 6. In order to verify the robustness and convergence ability of the VFF-RLS algorithm, this test is manually divided into two sections. The first section is called the data loss test section. In this section, five places of measured data of both current and voltage for one thousand seconds, are deleted manually in order to simulate a special situation that some data are missing or unrecorded in actual measurement. The data loss points are marked in Fig. 6, which time are at 1000 s, 2000 s, 3000 s, 4000 s and 5000 s. Because of the impact of these missing data, the parameter values around these points would change abruptly and the prediction error would be very large. Thus, the higher the robustness and convergence ability of the algorithm, the faster the identification results converges to the real parameter value.

The second section is named standard DST section. In this section, the profile of the current is in accordance with the DST which is a kind of standard operation conditions. The accuracy of the VFF-RLS which is under a normal battery working condition would be verified in this section.

This simulation is carried out in Matlab/Simulink software. The simulation platform is shown in Fig. 7.

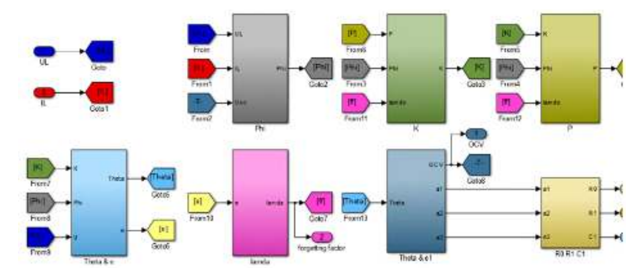

FIGURE 7. Parameter identification simulation platform.

The identification result of parameter OCV in RLS algorithm and VFF-RLS algorithm are shown in Fig. 8. The line in blue color and red color are the parameter identification results of OCV in these two methods respectively. And the green line is the true value of OCV.

In RLS algorithm, the forgetting factor λ is set to be 0.965, which is the best optimal value under this test. In VFF-RLS algorithm, the maximum value of the forgetting factor $\lambda_{\max}$ is also set to be 0.965 in order to have a comparison with RLS algorithm. The minimum value of the forgetting factor $\lambda_{\min}$ is 0.7 to improve the convergence ability of this algorithm. The sensitive gain ρ is set to be 12000 in order to ensure the sensitivity and stability of the algorithm. For the initial values of θ, the first element OCV is set to the initial terminal voltage 4.178, and another three elements α_1, α_2, and α_3 are 0.001. The subfigures (a) to (e) in Fig. 8 illustrate the identification results around the data loss points. It is easy to see that the VFF-RLS algorithm has greater convergence ability at the time of 1000 s, 2000 s and 4000 s, and it converges earlier about 60 s than RLS algorithm. At time of 3000 s, the prediction error of the VFF-RLS algorithm is accidentally not large, so there is no obvious difference between these two algorithms. At 5000 s, because of the accuracy of the algorithm itself, the true value of OCV is close to the identified value after the abrupt change. This situation also lead to a small prediction error. So the VFF-RLS algorithm and RLS algorithm have similar identification results around this point. The subfigure (f) shows a period of the parameter identification results in the standard DST section. The identification results of OCV in VFF-RLS algorithm and RLS algorithm have few differences in this section. While, close to the end of the test, the identification results of these two algorithms are slightly different. This is because that at the end of the test, the OCV drops rapidly and the identification accuracy of the algorithm itself is not high.

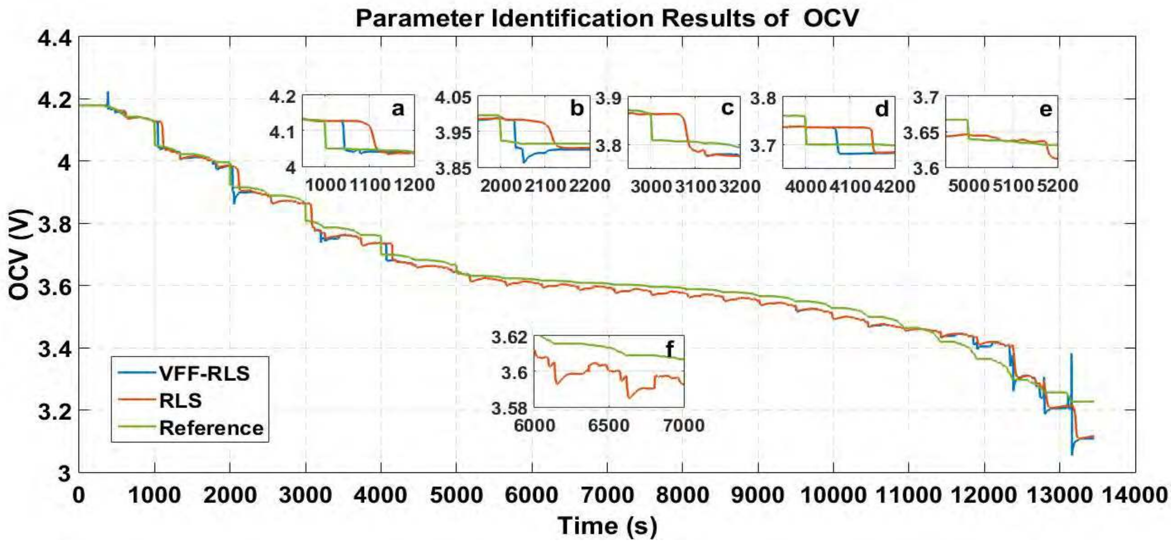

FIGURE 8. OCV identification results of data loss working condition test.

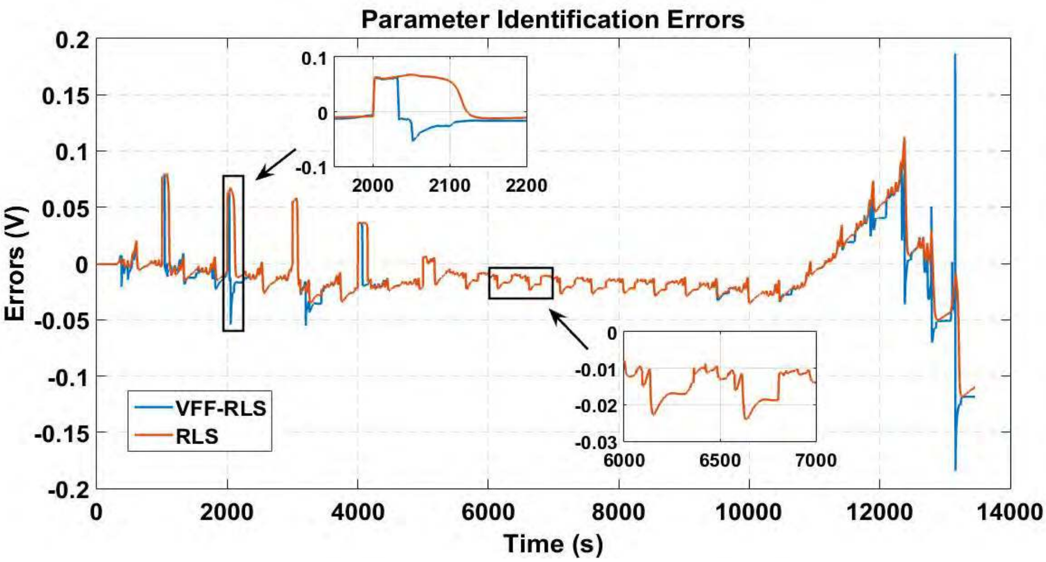

FIGURE 9. Parameter identification errors of OCV.

It can be concluded that, mostly, when the OCV changes drastically, meanwhile the signal is unstable or the system fails, the identification results in VFF-RLS algorithm can converge faster than in RLS algorithm. And after the convergence period, the estimated OCV value is close to the real value. The λ in VFF-RLS algorithm comes into a suitable value to ensure the accuracy of the algorithm.

The prediction errors' results of the RLS algorithm and VFF-RLS algorithm are shown in Fig. 9.

It can be seen from the Fig. 9 that the identification errors in VFF-RLS algorithm are lower than the errors in RLS algorithm in the data loss section. It is obviously that the errors of VFF-RLS could drop quickly after the data loss points to reduce the errors, because of the response of forgetting factors to that can be seen from Fig. 10. In addition, the performance of VFF-RLS algorithm is almost as good as RLS algorithm in the middle period of standard DST section. The identification errors of VFF-RLS are apparently larger than the errors of RLS algorithm at the end of the test. The errors root mean square (RMS) values of RLS algorithm and VFF-RLS algorithm are 0.0196 and 0.0227 in data loss section, 0.0181 and 0.0180 from 6000 s to 10000 s, 0.0479 and 0.0462 from 10000 s to 13458 s (the end of the test), 0.0296 and 0.0294 in the whole process. In standard DST section, especially in the end period of the test, the RLS algorithm has higher accuracy. This is because that 0.965 is the optimal value of the forgetting factor in DST test and the VFF-RLS algorithm is designed to adapt to different battery working conditions.

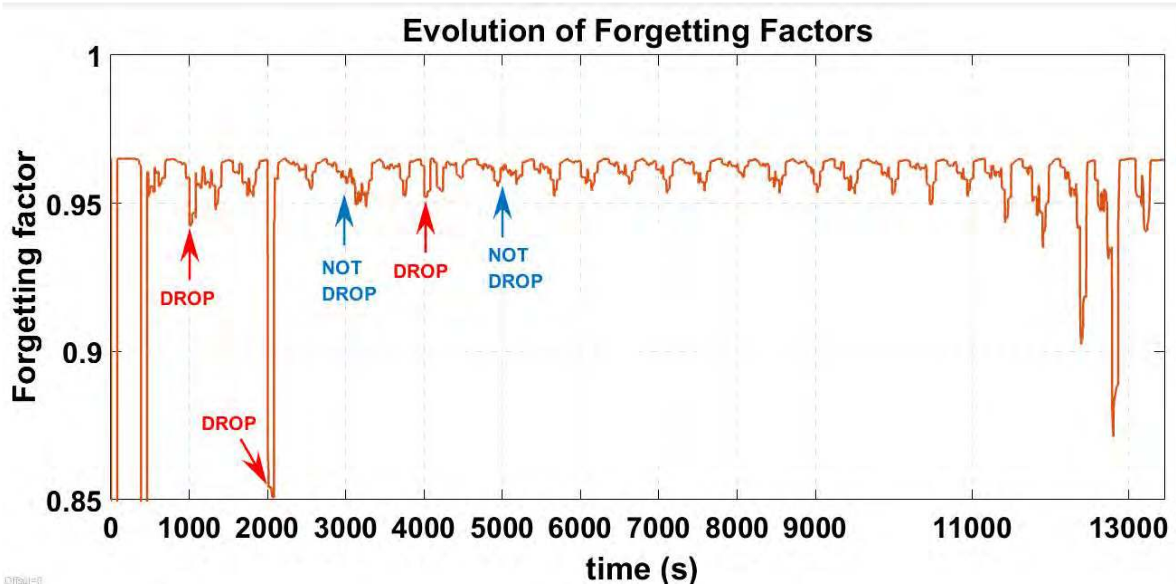

FIGURE 10. Evolution of forgetting factors under data loss working condition.

The accuracy of VFF-RLS algorithms is slightly lower than the RLS algorithm with the optimal forgetting factor in a specific working condition that is acceptable. In the data loss section, the accuracy of OCV identification is improved by the VFF-RLS algorithm and the signal disturbance is overcome. It can be concluded that the robustness of the RLS algorithm is improved by employing this novel variable forgetting factor method.

VI. CONCLUSION

In this paper, a novel variable forgetting factor method based on J.D. Park's research is provided. Several improvements are put forward by considering the practical application of lithium-ion battery model's parameter identification and some deficiencies of J.D. Park's method. Firstly, because computational differences between fractional-exponential and integer-exponential arithmetic in computers are not large, the NINT(x) function is removed. Secondly, comparing with the parameter identification results with different forgetting factors, 1 is not a suitable value of the maximum forgetting factor that is proved. The maximum value is replaced by λ_{max}. Additionally, in order to reduce the disturbance of a single data point, a moving data window is employed in this algorithm. The forgetting factor would be determined by the mean square value of the prediction errors in the window.

By the comparison between the VFF-RLS algorithm and the RLS algorithm, it can be concluded that: (1) The VFF-RLS algorithm has great performance in robustness and convergence ability when the signals are unstable. And it could converge to the true value more quickly than RLS algorithm. (2) If the prediction error is not large when the OCV changes drastically, the VFF-RLS's advanced convergence ability may become invalid. (3) Both the VFF-RLS algorithm and RLS algorithm have acceptable identification performance under standard and stable battery working conditions. Comparing to the RLS algorithm, the VFF-RLS algorithm can optimize the contradiction between the demand of fast convergence rate and the small parameter estimation error. In theory, the VFF-RLS algorithm should have higher accuracy in parameter identification than RLS algorithms and this would be verified further. This proposed VFF-RLS algorithm can feed its identification results to State of Charge and State of Health estimation in battery management system in electric vehicle and other systems requiring to online battery parameter identification, to enhance the anti-interference ability of these systems. Moreover, this variable forgetting factors can be used to other of RLS observers such as vector type RLS with multiple forgetting factors, and other equivalent circuit models of battery. For further research, this VFF-RLS algorithm can be optimized by evolution algorithm such as genetic algorithm and particle swarm optimization [16] and a quantity of experiment data of different working condition for higher adaptive ability in different working condition.

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