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RLS with Optimum Multiple Adaptive Forgetting Factors for SoC and SoH Estimation of Li-Ion Battery

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***Abstract*—Recursive least square (RLS) with a single forgetting factor has been commonly used for parameter and state estimation of dynamical systems. In many applications such as robotics, electric vehicles, renewable energy systems, and smart-grid, accurate battery state of charge (SOC) and state of health (SOH) estimation is essential for the safe and efficient operation. To this end, the challenge lies in identifying and parameterizing the temporal behavior of Lithium-Ion batteries, because their response is nonlinear and time-varying. This paper proposes a new RLS algorithm with optimum multiple adaptive forgetting factors (MAFFs) for SOC and SOH estimation of Li-ion batteries. Particle swarm intelligence is employed for identifying the system parameters. The performance of the optimum MAFF-RLS algorithm is compared to RLS with multiple fixed forgetting factors (MFFFs). Performance evaluation is carried out using the Urban Dynamometer Driving Schedule (UDDS). The simulation results indicate the better performance of MAFF-RLS algorithm compared to MFFF-RLS algorithm in terms of mean square error of SOC and internal resistance.**

Keywords—RLS; forgetting factor; Li-Ion; Battery; SOC; SOH

I. INTRODUCTION

In many applications such as robotics, electric vehicles, renewable energy systems, and smart-grid, battery state of charge (SOC) and state of health (SOH) have to be estimated accurately to ensure optimum and safe operation. The internal resistance and/or capacity values of the battery can be used as indicators of battery SOH. The challenge lies in the online parameter identification because Lithium batteries have time varying nonlinear dynamics.

Many battery SOC and SOH estimation methods have been proposed previously. In [1] a comprehensive review is provided of Lithium battery SOC and SOH estimation methods based on the adaptive systems formulation [1]. For SOC estimation, the Adaptive Unscented Kalman Filter (AUKF) achieved the best performance. AUKF was compared to the Extended Kalman Filter (EKF), Adaptive EKF, and Unscented Kalman filter (UKF), Artificial Neural Networks (ANN) and fuzzy logic. Although fuzzy logic performed well the memory requirements for describing the set of fuzzy rules were significantly larger compared to the rest methods.

Other concepts for battery SOC and SOH estimation based on Kalman filters have also been proposed [2] [3] [4]. An interesting one is the dual extended Kalman filters (Dual EKF) method. In dual-EKF, one EKF is performing the SOC estimation and the other the SOH estimation. The first EKF uses a model comprising the SOC, a hysteresis element and the parameters of the filter. The second EKF is based on a simple model where the internal resistance is modelled as a constant value [2]. In [3] a dual Kalman filter was combined with Support Vector Regression (SVR). A standard Kalman filter was employed for estimating the RC voltages and internal resistance, while an EKF was used for estimating SOC and the resistances of the RC circuits. The SVR was utilized to calculate the capacity of the battery. In [4] two EKFs were employed for SOC and SOH estimation [4]. The first EKF estimated in real-time the SOC, while the second EKF updated the internal resistance and capacity in an "off-line" manner.

Also, combinations of the least square (LS) algorithm with EKF were tested for battery SOC and SOH estimation [5] [6]. In [5] the EKF estimated the SOC and battery capacity. The RLS identified the parameters of the model employed by the EKF. A hybrid RLS-EKF method was proposed in [6]. A regression vector comprising previous terminal voltage differential, current and previous current differential values were used. The RLS identified the battery parameters values. An open circuit voltage (OCV) estimator provided estimates of the Voltage and current signals. For this purpose, a second order state equation, whose state variables were SOC and the inverse of battery capacity, was employed. The EKF estimated the SOC and battery capacity

Battery SOC and SOH estimation using the sliding mode observer technique is described in [7] [8]. In [7] a novel method combining LS, the adaptive discrete-time sliding mode observer (ADSMO) and a battery model comprising an enhanced Coulomb counting algorithm and an RC circuit was discussed. The LS algorithm identified the RC circuit model parameters. The sliding mode observer estimated the SOC. Subsequently, SOH was calculated using the SOC and the battery capacity. In [8] the dual adaptive sliding mode observer technique was proposed (Dual ASMO). The first SMO was designed based on 4 state equations in that described the terminal voltage, SOC, and 2 internal voltages of the RC circuit model. The second SMO was designed based on 2 state equations that described the terminal voltage and internal resistance [8].

The dual recursive least square (Dual RLS) algorithm was applied to the SOC and internal resistance estimation in [9]. Two different output voltage equations were used. The identification problem comprised seven parameters that were a function of voltage and current.

The previously mentioned methods are to a certain extent complex as they require the combination of two or more algorithms, i.e. Kalman filter, EKF, off-line LS, RLS with a single forgetting factor, SVR, and SMO. Moreover, some of them require off-line calibration which results in energy loss.

This paper proposes a new method of Li-ion battery SOC and SOH estimation using only one algorithm. The algorithm operates online and does not require off-line calibration. The proposed algorithm is based on the results of [10] [11] [12] and further developed. Battery SOC was estimated using RLS with multiple fixed forgetting factors (MFFF-RLS) and the Genetic Algorithm [10]. The Particle Swarm Optimization (PSO) was employed in [11] instead of the Genetic Algorithm. Estimation using RLS with multiple adaptive forgetting factors (MAFF-RLS) but with a constant internal resistance assumption was reported in [12]. The main contribution of this paper is the optimization of the coefficients that control the values of the multiple forgetting factors. Moreover, instead of making a constant internal resistance assumption, it is assumed to vary with SOC. The internal resistance value is used as a SOH indicator [13].

In section II, the battery model is described. RLS algorithm with multiple forgetting factors is revisited, and problem formulation is proposed. Section III presents a method for calculating the coefficients of forgetting factors based on Particle Swarm Optimization (PSO). Simulation results and discussion are reported in section IV. And lastly in section V the conclusion is drawn.

II. Modeling And Problem Formulation

A. Battery Equivalent Circuit Model

In this paper the equivalent circuit model using a single RC circuit is used, see Fig. 1 [10] [11]. V_t and I represent the battery terminal voltage and current, respectively. R_0 is the battery internal resistance, R_p is diffusion resistance, and C_p is diffusion capacitance. U_d denotes the voltage drop accross the diffusion resistance.

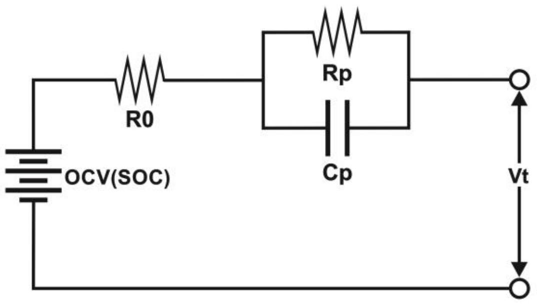

Fig. 1. Single RC equivalent circuit model.

The current is positive when it flows into the battery. The battery dynamics is expressed as follows:

$$U_d(k) = -a_1 U_d(k-1) + b_0 I(k) + b_1 I(k-1) \quad (1)$$

$$V_t(k) = U_d(k) + OCV(k) \quad (2)$$

Where:

$$R_0 = b_0;\ R_p = \left(\frac{b_1 - a_1 b_0}{1 + a_1}\right);\ C_p = \left(\frac{T}{b_1 - a_1 b_0}\right)$$

OCV is a non linear function of SOC [14]. Therefore, SOC can be derived from OCV. The battery internal parameters are dependent on SOC and they are time varying in nature.

Terminal voltage estimate $\hat{V}_t(k)$ is expressed in the following linear equation.

$$\hat{y}_k = \hat{V}_t(k) = \hat{\theta}_k^T x_k \quad (3)$$

Where regressor x_k and parameter estimates $\hat{\theta}_k$ are given below.

$$x_k = [U_d(k-1); I(k);\ I(k-1);\ 1]$$

$$\hat{\theta}_k = [-a_1(k);\ b_0(k);\ b_1(k);\ OCV(k)]$$

The measured terminal voltage is given as follows.

$$y_k = V_t(k) = \hat{V}_t(k) + e_k \quad (4)$$

B. Recursive Least Square with Multiple Forgetting Factors

It is stressed out that battery parameters change at different rates. To cope with this issue, it is proposed to employ RLS with multiple forgetting factors. A method of battery SOC and SOH estimation using optimum RLS with multiple fixed forgetting factors has already been published [11].

Fixed forgetting factor implies that the system dynamics is invariable, not depending on time. A smaller forgetting factor yields faster tracking of parameter changes. On the other hand, faster tracking may lead to instability. In order to cope with this trade-off issue, variable forgetting factor is needed. In this paper, the RLS with multiple adaptive forgetting factors (MAFF-RLS) is adopted [12]. However, in this study a different hypothesis is made. Instead of assuming the internal resistance is constant, it is set as a function of SOC. SOH estimation performance can be evaluated base on the internal resistance change tracking capability.

Refer to Fortescue's modified equation [15], the following variable forgetting factor is used.

$$\lambda_{i,k} = 1 - \frac{1}{1 + \frac{\mu_i}{x_{i_k}^2 P_{i_{k-1}}}} \quad (5)$$

Where subscript i indicates scalar components $i = 1, 2 \ldots n$. In this paper $n = 4$. $\lambda_{i,k}$ and $P_{i_{k-1}}$ denote forgetting factor of the i-th parameter at time k, and the i-th parameter covariance at the previous time step, respectively. μ_i is a constant. Procedure of the MAFF-RLS is described as follows [12].

$$e_k = y_k - x_k^T \hat{\theta}_{k-1} \quad (6)$$

$$K_{i_k} = \frac{P_{i_{k-1}} x_{i_k}}{\lambda_{i,k} + x_{i_k}^T P_{i_{k-1}} x_{i_k}} \quad (7)$$

$$P_{i_k} = \frac{1}{\lambda_{i,k}}\left(1 - K_{i_k} x_{i_k}^T\right) P_{i_{k-1}} \quad (8)$$

$$\hat{\theta}_k = \hat{\theta}_{k-1} + L_k e_k \quad (9)$$

where L_k is the updated gain of the whole parameters vector $\hat{\theta}_k$ which is given below.

$$L_k = \frac{1}{1+\frac{P_{1_{k-1}} x_{1_k}^2}{\lambda_{1,k}}+\frac{P_{2_{k-1}} x_{2_k}^2}{\lambda_{2,k}}+\dots+\frac{P_{i_{k-1}} x_{i_k}^2}{\lambda_{i,k}}} \begin{bmatrix} \frac{P_{1_{k-1}} x_{1_k}}{\lambda_{1,k}} \\ \frac{P_{2_{k-1}} x_{2_k}}{\lambda_{2,k}} \\ \vdots \\ \frac{P_{i_{k-1}} x_{i_k}}{\lambda_{i,k}} \end{bmatrix} \quad (10)$$

C. Problem Formulation

The following performance index is applied to assess the MAFF-RLS algorithm.

$$J_0 = \frac{1}{N_s}\sum_{k=1}^{N_s}\left\{V_t(k) - \hat{V}_t(k)\right\}^2 \quad (11)$$

In order to minimizes mean square error values of both OCV and internal resistance, the following objective function is proposed.

$$F_t = \alpha F_1 + (1-\alpha)F_2 \quad (12)$$

$$F_1 = \frac{1}{N_s}\sum_{k=1}^{N_s}\left(1 - \frac{OCV(k)}{OCV^*(k)}\right)^2 \quad (13)$$

$$F_2 = \frac{1}{N_s}\sum_{k=1}^{N_s}\left(1 - \frac{R_0(k)}{R_0^*(k)}\right)^2 \quad (14)$$

$$0 < \alpha < 1 \quad (15)$$

OCV^* and R_0^* represent true values of OCV and internal resistance, respectively. The objective function in equation (14) is a sum of the weighted normalized fitness functions F_1 and F_2. Input to the sysem is current load with urban dynamometer driving schedule (UDDS) profile.

Problem of determining optimum MAFF-RLS is formulized in equation (16).

$$\left.\begin{array}{c} Find\ \{\alpha, \mu_i\}\ which: \\ Minimize\ \ F_t(\alpha, \mu_i) \\ Where: \\ \{0 < \alpha < 1\}\ and\ \{0 < \mu_i < 1\} \\ I(k)\ is\ generated\ by\ UDDS \end{array}\right\} \quad (16)$$

III. Optimization Method Using PSO

The optimization problem is solved using Particle Swarm Optimization (PSO), a powerful population-based optimization technique. Fig. 2 shows block diagram of the proposed method.

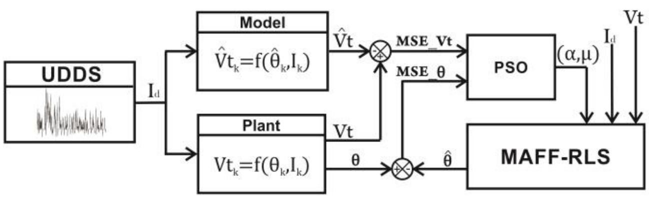

Fig. 2. Optimization method of MAFF-RLS.

PSO is a kind of evolutionary computation techniques which resembles social behaviour of fish schooling or bird flocking. Its basic conceptual framework was originally proposed in 1995 [16]. In PSO, a particle represents a solution, and a swarm of particles is refered to as population of solutions. Each particle is characterized by its velocity and position. Every time a new position is achieved the best positions and velocities are updated. Each particle adjusts its velocity based on its experiences.

The following equations are used in PSO to find optimum values of weight and coefficient of forgetting factors.

$$\lambda_0^i = \lambda_{min} + Rand(\lambda_{max} - \lambda_{min}) \quad (17)$$

$$v_0^i = \frac{\lambda_0^i}{t_s} \quad (18)$$

$$v_{k+1}^i = w v_k^i + c_1 Rand\left(\frac{p^i - \lambda_k^i}{t_s}\right) + c_2 Rand\left(\frac{p_k^g - \lambda_k^i}{t_s}\right) \quad (19)$$

$$\lambda_{k+1}^i = \lambda_k^i + v_{k+1}^i t_s \quad (20)$$

λ_k^i and v_k^i represent the i^{th} particle at time k of the positions and velocities, repectively. The upper and lower bounds on the positions are denoted by λ_{max} and λ_{min}. *Rand* is a uniformly distributed random variable. t_s denotes a positive scalar. The initial positions λ_0^i and initial velocities v_0^i are randomly generated. p^i is the best positions of each paticle over time in curent and all previous moves. p_k^g is the best global positions of a certian particle in the current swarm in respect to the fitness function. The new search direction encorporates three pieces of information which has each own weight factor. The first part is current motion which is multipied by its inertia factor w. The second part is particle memory influence which is multiplied by its cognitive factor c_1, and the third part is swarm influence which is multiplied by its social factor c_2.

In order to thoroughly explore the best solution, 27 sets of PSO factors (w, c_1, c_2) were randomly generated according to three range categories i.e. low (L), medium (M), and high (H) as listed in Table 1. The values for which the objective function achieves the minimum value is the solution.

TABLE I. Category of PSO Factors

		Factor		
		w	c_1	c_2
Category	L	$0.1 \le w < 0.4$	$0.1 \le w < 0.7$	$0.1 \le w < 0.7$
	M	$0.4 \le w < 0.7$	$0.7 \le w < 1.4$	$0.7 \le w < 1.4$
	H	$0.7 \le w \le 1$	$1.4 \le w \le 2$	$1.4 \le w \le 2$

IV. Results and Discussion

Computer simulation were conducted. The swarm size was 64. Fitness function tolerance was 10^{-6}. The stall iteration limit was 50. Fig. 3 shows the convergence of objective function F_t as a function of 27 different factors values.

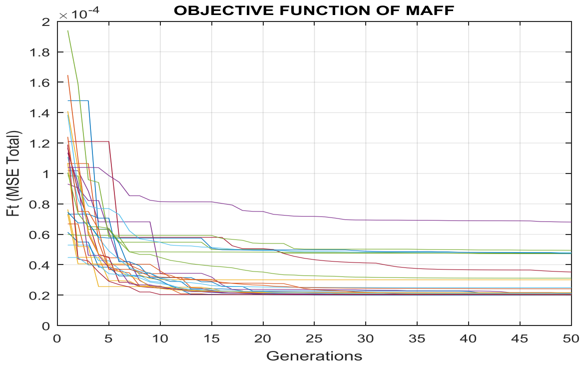

Fig. 3. Convegrnece history of objective function F_t

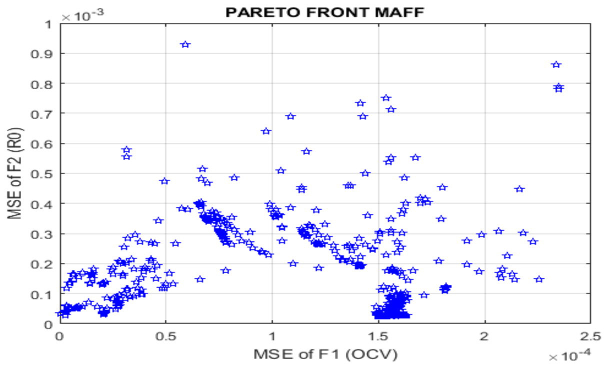

Fig. 4. Plot of fitness functions F_1 and F_2

The minimum fitness function F_t is selected, and the corresponding fitness function weight as well as forgetting factor constants are identified. Fig. 4 plots the distribution of fitness function values F_1 and F_2. Table 2 lists up the coefficient of forgetting factor μ_i, which was obtained by the proposed method. For comparison study, MFFF-RLS algorithm has also been optimized under the same condition. The optimal forgetting factor value λ_i is also listed up in Table II.

TABLE II. Parameters Values Obtained Through Optimization

MAFF	μ_1	μ_2	μ_3	μ_4	α
	0.01	0.1791	0.025	0.0316	0.1111
MFFF	λ_1	λ_2	λ_3	λ_4	α
	0.9476	0.9882	0.9249	0.8523	0.1

The obtained parameters values in Table II were implemented into MAFF-RLS and MFFF-RLS for state and parameter estimation under UDDS testing for a period 6.5 hours. The initial value of estimated SOC value was intentionaly set to 100% to provide 5% offset (estimation error). Fig. 5 shows time history of battery terminal voltage (upper figure) and its estimation error (lower figure) during the UDDS testing using the coefficients and forgetting factors listed in table 2. Red broken line is the results of MAFF-RLS, and the blue broken line is the results of MFFF-RLS. Fig. 6 shows the corresponding SOC (upper figure) and its estimation error (lower figure). From these figures, it is observed that MAFF-RLS achieves better performance than MFFF-RLS, considering the battery terminal voltage and SOC estimation.

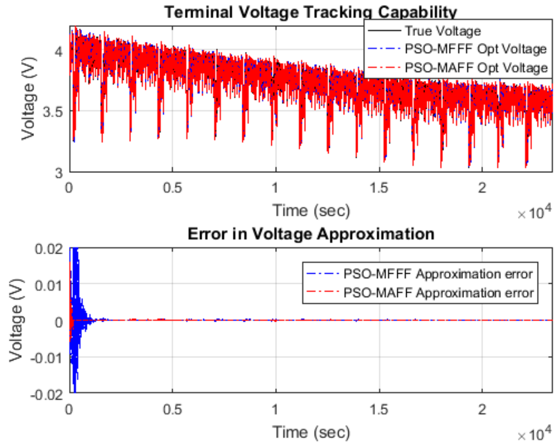

Fig. 5. Terminal voltage and its estimation.

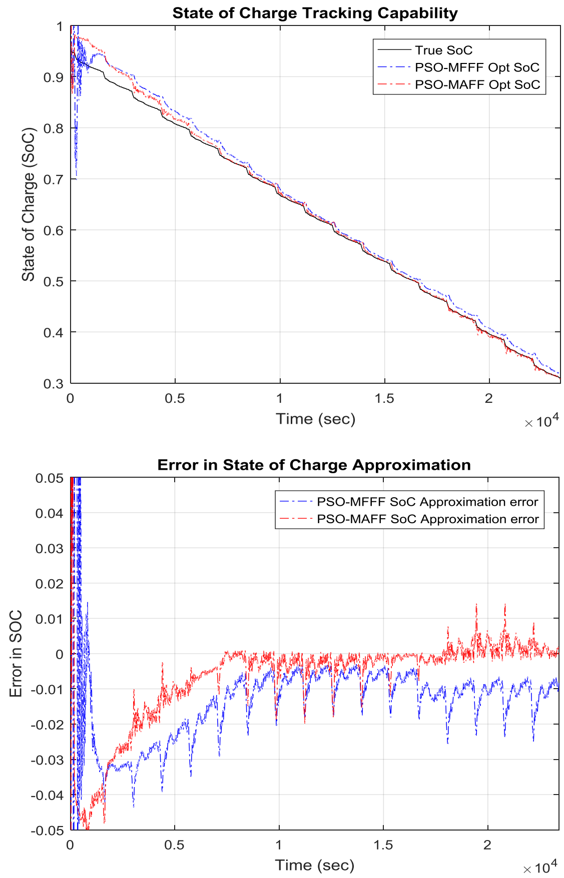

Fig. 6. Time history of state of charge and its error.

Fig.7 illustrates the time history of internal resistance estimate $\hat{R}_0(k)$ (upper figure) and its estimation error (lower figure). The initial internal resistance is 19.13 (mΩ). It is obvious that the designed MAFF-RLS can estimate internal resistance value better than the MFFF-RLS.

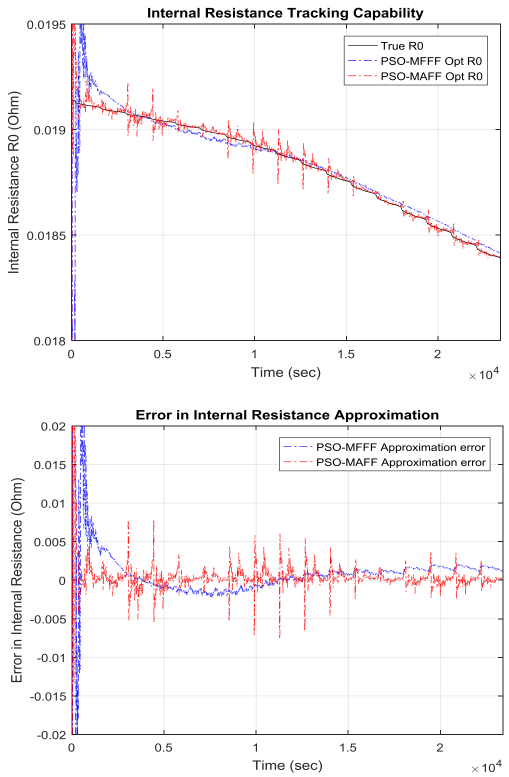

Fig. 7. Estimated internal resistance.

Table 3 lists the estimation error as performance index obtained from these results. J_1 and J_2 represent the mean square error (MSE) of SOC and internal resistance, respectively. It is obvious that MAFF-RLS gives better estimation performance than MFFF-RLS in terms of SOC and internal resistance estimation. The internal resistance estimation is used as the SOH indicator.

TABLE III. PERFORMANCE INDEX VALUE

No	Performance Index	Values	
		MAFF-RLS	**MFFF-RLS**
1	J_0	6.8003e-08	2.7888e-05
2	J_1	3.9769e-05	2.5560e-04
3	J_2	6.1415e-09	2.2572e-08

V. CONCLUSION

Based on the results the following conclusion can be drawn. The proposed designed method, called optimum MAFF-RLS, can real-time estimate both SOC and SOH of Li-ion battery. Under UDDS testing for a period 6.5 hours with an initial 5% offset in the SOC value, the proposed algorithm tracked both SOC and internal resistance variations with a very good accuracy. The MSE was 3.98×10^{-5} for SOC, and 6.14×10^{-6} mΩ for the internal resistance, respectively. The proposed MAFF-RLS achieves better estimation performance of battery SOC and SOH than the MFF-RLS.

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