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Quadruple Adaptive Observer of the Core Temperature in Cylindrical Li-ion Batteries and their Health Monitoring

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Abstract— **Temperature monitoring is a critical issue for lithium ion batteries. Since only the surface temperature of the battery can be measured, a thermal model is needed to estimate the core temperature, which can be higher and hence more critical. In this paper, an on-line parameter identification scheme is designed for a cylindrical lithium ion battery thermal model, by which the parameters of the thermal model can be identified automatically. An adaptive observer is designed based on the on-line parameterization methodology and the closed loop architecture. A linear battery thermal model is explored first, where the internal resistance is assumed to be constant. The methodology is later extended to address temperature dependent internal resistance with non-uniform forgetting factors. The capability of the methodology to track the long term variation of the internal resistance is beneficial for battery health monitoring.**

I. INTRODUCTION

Lithium ion batteries have been widely considered as an energy storage device for hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEV). Thermal management is a critical issue for onboard lithium ion batteries due to their narrow window of operating temperatures. An accurate prediction of the battery temperature is the key to an effective thermal management system and to maintain safety, performance, and longevity of these Li-Ion batteries.

Some of the previous works on thermal modeling and management predict the detailed temperature distribution throughout the cell [1], [2], [3], [4], but are not suitable for onboard application due to high computational intensity. Others use one single temperature to capture the lumped thermal behavior of the cell [5], [6], [7]. Even though the single temperature approximation is computationally efficient, it might lead to over-simplification since the temperature in the core of the cell can be much higher than in the surface [8]. It is in the core where major battery thermal breakdown and degradation occurs.

Lumped thermal models capturing both the surface and the core temperatures of the cell have also been studied in [8] and [9]. Such simplified models are efficient for onboard application due to their limited number of states. In addition to the higher fidelity of the two-state model, the prediction of the surface temperature can be compared with the measured value, and the errors can be fed back to correct the core temperature estimation. The accuracy of the model parameters is of great importance since it determines the precision of the core temperature estimation. Model parameters can be approximated by correlating to the geometry of the battery and the physical properties of all its components [9], but such approximation may not be accurate due to the complicated layered structure of the cell and the interface resistance between the layers. The parameters can also be determined by fitting the model to the data obtained from designed experiments [8], [9]. However, some of the thermal parameters, such as the internal resistance, may change over the battery lifetime due to degradation, and thus need to be identified continuously.

An online parameterization scheme is designed in this paper to automatically identify the thermal model parameters based on the commonly measured signals in vehicle battery systems. Based on the online identifier, an adaptive observer is then designed for core temperature estimation. A linear battery model with constant internal resistance is investigated first, where the pure least square algorithm is sufficient for identification. When the internal resistance of the battery is non-constant, e.g. temperature dependent [5], [10], a non-uniform forgetting factora is utilized to identify the time-varying resistance. The internal resistance of the lithium ion battery may increase over lifetime due to degradation as the solid electrolyte interphase (SEI) grows in thickness [11], [12]. The least square algorithm with non-uniform forgetting factors is also explored to track the long term growth of the internal resistance. The growth of the internal resistance greatly affects the power capability, and can be viewed as an indication of the battery state of health (SOH).

II. LUMPED THERMAL MODEL OF A CYLINDRICAL LITHIUM ION BATTERY

A cylindrical battery is modeled with two states [9], namely the surface temperature T_s and the core temperature T_c, as shown in Fig. 1. The governing equations for the single cell thermal model are defined as [9],

$$C_c\dot{T}_c = I^2R_e(T_c) + \frac{T_s - T_c}{R_c}, \quad C_s\dot{T}_s = \frac{T_f - T_s}{R_u(V)} - \frac{T_s - T_c}{R_c}. \quad (1)$$

In this model, heat generation is approximated by a concentrated source of Joule loss in the battery core, computed as the product of the current I squared and an internal resistance R_e. The internal resistance R_e is modeled as temperature dependent[5], [10], and described here as

$$R_e = -0.00027T_c^3 + 0.032T_c^2 - 1.22T_c + 19.8, \quad (2)$$

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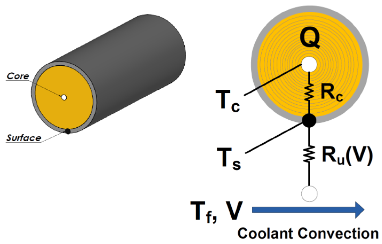

Fig. 1. Single Cell Lump Parameter Thermal Model

where R_e is in $m\Omega$ and T_c is in ^oC. Heat exchange between the core and the surface is modeled by heat conduction over a thermal resistance, R_c, which is a lumped parameter including both the conduction and contact thermal resistance. A convection resistance R_u is modeled between the surface and the surrounding coolant to account for convective cooling. The value of R_u is a function of the coolant flow velocity V, as described in [13], [14]

$$R_u = \frac{D}{k\overline{Nu}A}, \quad \overline{Nu} = qRe^m Pr^{0.36}, \quad Re = \frac{VD}{\nu}, \tag{3}$$

where D is the diameter of the battery, A is the surface area of the battery, k is the thermal conductivity of the coolant, $\overline{Nu}$ is the Nusselt number, Re is the Reynolds number, Pr is the Prandtl number and ν is the kinematic viscosity. These quantities are related to the physical properties of the coolant and the geometries of the battery pack, such as the spacing between cells. They can be calculated for specific type of coolant and battery pack configuration. Values of coefficients m and q for various Re ranges can be found in [13], [14]. The rate of temperature change of the surface and the core depends on their respective lumped heat capacities. The parameter C_c is the heat capacity of the jelly roll inside the cell, and C_s is related to the heat capacity of the battery casing.

The complete parameter set for this model includes C_c, C_s, R_e, R_c, and R_u. Model identification techniques will be developed to obtain parameter values based on measurable inputs and outputs of the model. The thermal model in Eq. (1) is a nonlinear model since R_e is a function of T_c, and R_u depends on V. Such nonlinearity, especially in R_e, complicates the parameter identification. For simplicity, a thermal model with constant R_e is investigated first, and the methodology will then be extended to account for the full nonlinear model.

III. Parameterization Methodology

For model identification, a parametric model

$$z = \theta^T \phi \tag{4}$$

is derived first by applying Laplace transformation to the model, where z is the observation, θ is the parameter vector and ϕ is the regressor [15]. Both z and ϕ should be measured or can be generated from measured signals.

With a parametric model, various algorithms can be chosen for parameterization, such as the gradient search and the least squares. The method of least squares is preferred here due to its advantages in noise reduction [15].

The recursive least squares algorithm is applied in an online fashion, where parameters are updated continuously [15]

$$\begin{aligned} \dot{\theta}(t) &= P(t)\frac{\varepsilon(t)\phi(t)}{m^2(t)}, \quad \dot{P}(t) = -P(t)\frac{\phi(t)\phi^T(t)}{m^2(t)}P(t) \\ \varepsilon(t) &= z(t) - \theta^T(t)\phi(t), \quad m^2(t) = 1 + \phi^T(t)\phi(t), \end{aligned} \tag{5}$$

where m(t) is the normalization factor to enhance the robustness of parameter identification.

In some cases, to make the observation z and the regressors ϕ proper (or causal), a filter $\frac{1}{\Lambda(s)}$ will have to be designed and applied. The parametric model will then become

$$\frac{z}{\Lambda} = \theta^T \frac{\phi}{\Lambda}. \tag{6}$$

IV. Parameterization of the Thermal Model with Constant R_e and Adaptive Observer Design

In this section, a parameterization scheme and adaptive observer is designed for the battery thermal model with constant internal resistance R_e.

A. Parameterization Design

The inputs are the current I, the coolant temperature T_f, and the coolant velocity V. The measurable output is the battery surface temperature T_s. A parametric model can be derived by performing Laplace transformation on Eq. (1), and substituting unmeasured T_c by measured I, T_f, V and T_s,

$$\begin{aligned} s^2T_s - sT_{s,0} = &\frac{R_e}{C_cC_sR_c}I^2 + \frac{1}{C_cC_sR_c}\frac{T_f - T_s}{R_u(V)} \\ &- \frac{C_c + C_s}{C_sC_cR_c}s(T_s - T_{s,0}) + \frac{1}{C_s}s\frac{T_f - T_s}{R_u(V)}, \end{aligned} \tag{7}$$

where $T_{s,0}$ is the initial surface temperature. It is noted that the initial core temperature is considered as equal to the initial surface temperature as if the battery starts from rest.

For the parametric model in Eq. (7), we have

$$\begin{aligned} z &= s^2T_s - sT_{s,0}, \quad \theta = [\alpha \quad \beta \quad \gamma \quad \mu]^T \\ \phi &= [I^2 \quad \frac{T_f - T_s}{R_u(V)} \quad sT_s - T_{s,0} \quad s\frac{T_f - T_s}{R_u(V)}]^T \end{aligned} \tag{8}$$

where $\alpha = \frac{R_e}{C_cC_sR_c}$, $\beta = \frac{1}{C_cC_sR_c}$, $\gamma = -\frac{C_c+C_s}{C_cC_sR_c}$, and $\mu = \frac{1}{C_s}$. It is noted that $\frac{T_f - T_s}{R_u(V)}$ is treated as a whole as a regressor, since T_f and T_s can both be measured, and R_u can be calculated based on knowledge of V using Eq. (3). With α, β, γ and μ identified, C_c, C_s, R_e, and R_c can be obtained by

$$C_c = -\frac{\gamma}{\beta} - \frac{1}{\mu}, C_s = \frac{1}{\mu}, R_e = \frac{\alpha}{\beta}, R_c = -\frac{\mu^2}{\gamma\mu + \beta}. \tag{9}$$

A second order filter should be applied to the signals in Eq. (7) to make them proper. The filter takes the form

$$\frac{1}{\Lambda(s)} = \frac{1}{(s+\lambda_1)(s+\lambda_2)}, \tag{10}$$

where λ_1 and λ_2 are designed based on the input and system dynamics. The least squares algorithm in Eq. (5) can then be applied for parameter identification.

B. Adaptive Observer Design

It is a common practice to design a closed loop observer to estimate the unmeasurable states of a system based on the measurable outputs. The observer for a linear system

$$\dot{x} = Ax + Bu, \quad y = Cx + Du \tag{11}$$

takes the form [16]

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - \hat{y}), \quad \hat{y} = C\hat{x} + Du, \tag{12}$$

where x and y are the actual system states, $\hat{x}$ and $\hat{y}$ are estimated states and output, L is the observer gain, and A, B, C and D are model parameters. The difference between the measured and the estimated output is used as the feedback to correct the estimated states.

Comparing with an open loop observer (observer without output injection), the closed loop observer can accelerate the convergence of the estimated states to that of the real plant under uncertain initial conditions, e.g. a Luenberger observer [16], or optimize the estimation by balancing the effect of process and measurement noises, e.g. a Kalman filter [17].

For the cylindrical battery thermal model in Eq. (1),

$$x = [T_c \quad T_s]^T, \quad y = T_s, \quad u = [I^2 \quad \frac{T_f - T_s}{R_u(V)}]^T$$
$$A = \begin{bmatrix} -\frac{1}{R_cC_c} & \frac{1}{R_cC_c} \\ \frac{1}{R_cC_s} & -\frac{1}{C_sR_c} \end{bmatrix}, B = \begin{bmatrix} \frac{R_e}{C_c} & 0 \\ 0 & \frac{1}{C_s} \end{bmatrix}, C = [0 \quad 1], D = 0. \tag{13}$$

An adaptive observer is designed based on certainty equivalence principle [15], where the estimated parameters from on-line identification in Eq. (5) are adopted for the observer. The structure of the whole on-line identification scheme and adaptive observer is shown in Fig. 2.

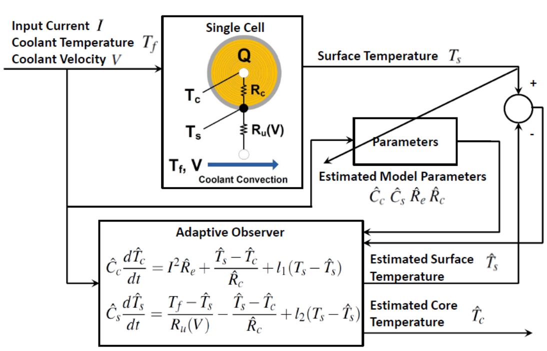

Fig. 2. On-line Identification Scheme and Adaptive Observer Structure

As shown in Fig. 2, when the thermal management system is operating in real time, the input current I, coolant temperature T_f and the measured surface cell temperature T_s are fed into the parameter identifier to estimate model parameters R_u, R_e and R_c. The adaptive observer, on one hand, adopts the estimated parameters for temperature estimation, and on the other hand, takes the errors between the measured and the estimated T_s as a feedback to correct its core temperature and surface temperature estimation. The estimations for both parameters and temperatures are updated at each time step.

TABLE I
NOMINAL VALUES OF PARAMETERS AND INITIAL GUESS FOR IDENTIFICATION

Parameters	$C_c(JK^{-1})$	$C_s(JK^{-1})$	$R_e(m\Omega)$	$R_c(KW^{-1})$
Nominal Values	268	18.8	3.5	1.266
Initial Guess	100	50	1	0.5

V. SIMULATION VERIFICATION

Simulation has been conducted to verify the designed parameterization scheme and adaptive observer. A cylindrical battery thermal model with parameters for an $A123$ 32157 $LiFePO4$/graphite battery is used to generate data for verification of the methodology. Parameters are assumed by scaling up values from [8] and [18]. Nominal values of the model parameters are listed in Table I.

The main purpose of the simulation here is to check whether the designed algorithm can be applied to identify those assumed parameters and estimate core temperature T_c, and thus resonable values of the assumed model parameters are sufficient.

A driving cycle with high power excursion, the Urban Assault Cycle (UAC) [19], is adopted as the current excitation for the simulation. The *UAC* cycle and the coolant flow velocity profile are shown in Fig. 3. The output of the model, T_s is also plotted in the bottom plot of Fig. 3. The air flow temperature is fixed at 25^oC.

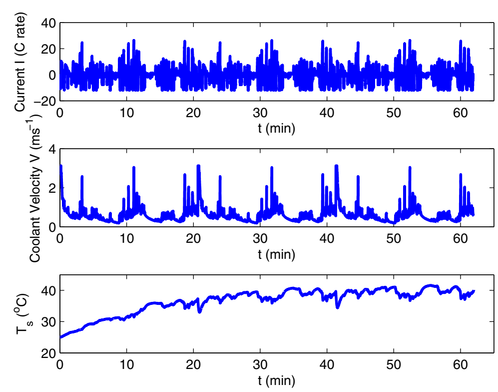

Fig. 3. Simulated Current and Coolant Velocity Inputs and Surface Temperature Output for Identification

The generated signals I, V and T_s are used for on-line least squares parameterization. The four parameters to be identified, C_c, C_s, R_e and R_c, are initialized with the values in Table I, which are quite away from the nominal values listed in the same table.

The on-line identification results are plotted in Fig. 4. It can be seen that all the 4 parameters converge to the nominal values in Table I.

The response of the adaptive observer, which adopts the identified parameters by online parameterization, is plotted in Fig. 5. In Fig. 5, the T_c and T_s simulated by the model are

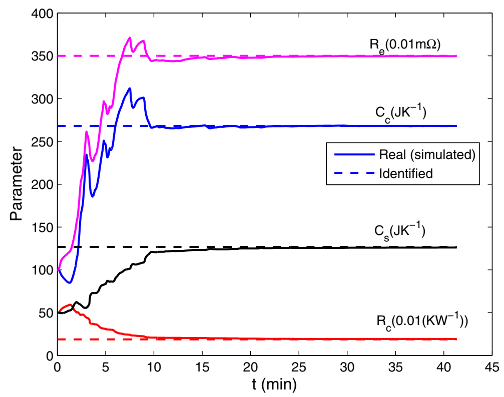

Fig. 4. Online Parameter Identification Results

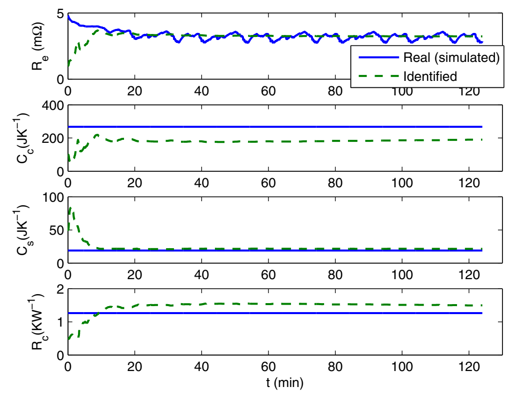

Fig. 6. Identification Errors when Eq. (5) is Applied Directly to Model with varying R_e

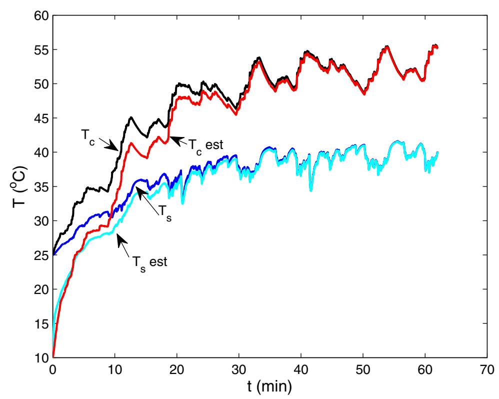

Fig. 5. Adaptive Observer Response

presented and the estimated T_c and T_s are plotted to evaluate the performance of the adaptive observer. The simulated core temperature T_c and surface temperature T_s are initialized to be 25^oC and the adaptive observer is preset to start from 10^oC for both the surface and the core temperatures. It can be seen that the convergence rate of the surface temperature T_s is independent of that of the parameters because it is directly measured and fed back to the observer. However, the convergence of the unmeasured core temperature T_c depends on the convergence of the parameters. As can be seen in Fig. 4, the identified T_c converges to the simulated T_c after the identified parameters converge to the right values.

VI. Parameterization of the Battery Thermal Model with Temperature Dependent R_e

When the battery internal resistance R_e is a function of the core temperature T_c, such as in Eq. (3), the parametric model in Eq. (7) will no longer be linear and thus direct application of the identification algorithm in Eq. (5) will result in biased estimation of the parameters, as shown in Fig. 6.

It can be seen from Fig. 6 that when R_e is a function of T_c, it will be time-varying since T_c is fluctuating all the time. The least square algorithm in Eq. (5) can only address parametric models with constant parameters, and its estimation can only converge to constant values if the stability conditions are satisfied. As a result, although the real R_e is varying, the value identified by Eq. (5) tends to track its average value. This will not only introduce errors in R_e estimation but will also affect the estimation of other constant parameters. As shown in Fig. 6, significant errors can also be observed for the estimation of the constant parameters C_c, C_s and R_c. Such errors are introduced because the least square algorithm aims at minimizing the errors in the model output estimation by finding a set of optimal parameters. However, in this case, since the errors in R_e identification are inevitable, the other parameters will also have to be biased to minimize the overall errors in T_s estimation. Such biased parameterization will corrupt the estimation of the core temperature T_c without causing large errors in the estimated surface temperature T_s, as shown in Fig. 7.

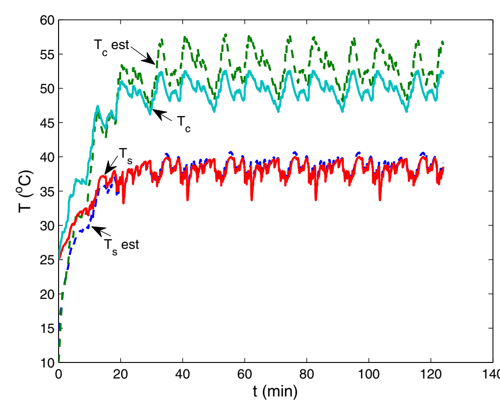

Fig. 7. Errors in T_c Estimation Brought by Biased Parameters

Such problem can be addressed by treating R_e as a time varying parameter and using forgetting factors in identification. When forgetting factors are adopted, the least square algorithm can be modified by using

$$\dot{P}(t) = \eta^T P(t)\eta - P(t)\frac{\phi(t)\phi^T(t)}{m^2(t)}P(t), \qquad (14)$$

as the covariance matrix dynamics in Eq. (5), where η is the forgetting factor matrix [15].

The least square identification algorithm tries to find the optimal parameters that best fit the inputs and outputs over the whole data set. A pure least square algorithm treats each data point with equal weight, no matter if it is acquired most recently, or obtained some time earlier. However, when a forgetting factor is applied, the data points will be weighted differently. Specifically, the newly acquired data are favored over the older ones. In the form shown in Eq. (14), the weight of the data will decay exponentially with the time elapsed, and the larger the forgetting factor is, the faster such decay will be. Consequently, the least square algorithm will update its results of identification primarily based on the recent data fed into it and thus can track the parameters when they are time-varying.

The least square algorithm with forgetting factors can be applied directly to the original linear parametric model in Eq. (7). Of the four lumped parameters, namely α, β, γ and μ in Eq. (7), since only α is related to time varying R_e, and all the others are constant, non-uniform forgetting factors should be adopted here. The η matrix is designed as $diag(\eta_1, 0, 0, 0)$, where η_1 is the forgetting factor associated with α (and hence R_e).

Simulation is conducted with $\eta_1 = 0.35$, and the results of identification are shown in Fig. 8. It is noted that the identified R_e can now follow the real varying R_e, and as a result, there is no bias in the estimation of the other constant parameters. Consequently, with the identified parameters, the adaptive observer can now estimate the battery core temperature T_c accurately even when the internal resistance R_e is temperature dependent, or a function of other variables, such as SOC. as shown in Fig. 9.

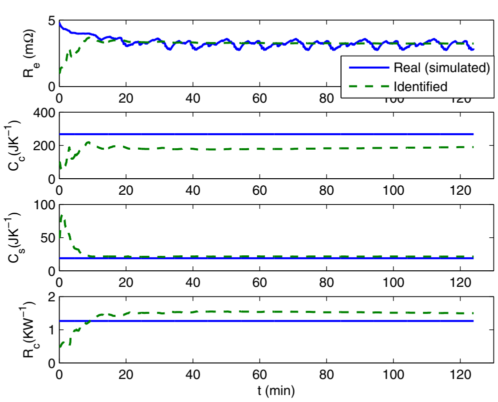

Fig. 8. Identification of Temperature Dependent Internal Resistance by the Least Square Algorithm with Non-uniform Forgetting Factors

VII. Degradation Detection by Monitoring Growth in Internal Resistance

The recursive least square algorithm with forgetting factors can also track the long term growth of the internal resistance, which can be used as an indication for the state of health (SOH) of the battery.

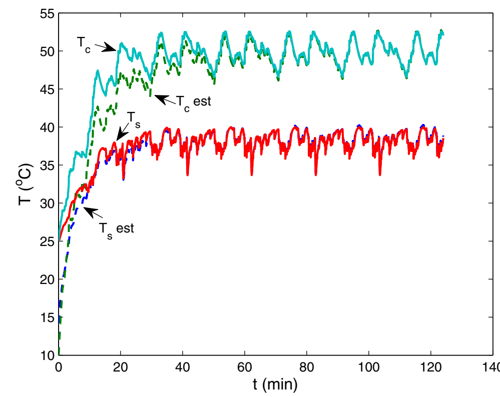

Fig. 9. Adaptive Estimation of Battery with Temperature Dependent Internal Resistance by Forgetting Factors

Different from the variation of the internal resistance caused by the fluctuation in the core temperature of the battery, the growth of the internal resistance due to degradation is a process that occurs slowly over the battery lifetime. The internal resistance might increase substantially over hundreds of current cycles or days according to [11], [20] and [12].

In this paper, the growth in internal resistance due to degradation is simulated and used to test the capability of the identification algorithm to detect the slow increase of the resistance. The internal resistance R_e, originally a function of the core temperature T_c, is now augmented with a term which is linearly increasing over time. The drive cycle used for simulation is the same UAC cycle shown in Fig. 3, but is repeated for 500 times and the rate of growth in internal resistance is set at 0.17%/cycle. The rate of degradation may also increase with the temperature according to [11], [20] and [12]. This effect is not considered here since the main purpose of the simulation is to test the identification algorithm.

The results of the online identification are shown in Fig. 10. It can been seen from Fig. 10 that the real internal resistance (simulated) gradually increases over time and is subject to short-term variation due to the fluctuation of the battery core temperature. The identified R_e follows both the long-term and short-term variation of the real one with a small delay as shown in the inset of Fig. 10. In real vehicle application, since R_e is varying all the time, it is difficult to evaluate SOH by the instantaneous value of R_e. Therefore, the averaged R_e might be a better choice instead. The mean value of R_e for each UAC cycle is plotted in the lower half of Fig. 10. It is noted that the averaged R_e can capture the long-term increase of the internal resistance and the identified value is a good estimation of the real one.

VIII. Conclusions and Future Work

The core temperature of a lithium ion battery, which is usually not measurable, is of great importance to the onboard battery management system, especially when the batteries are subject to high C-rate. The core temperature can be estimated by a two states thermal model, and the

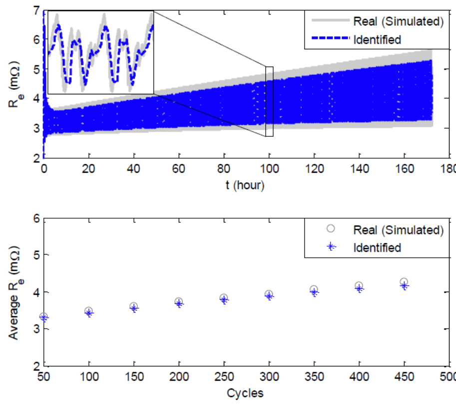

Fig. 10. Identification of Internal Resistance Subject to Degradation

parameters of the models are critical for the accuracy of the estimation. In this paper, an online parameter identification scheme based on least square algorithm is designed for the cylindrical lithium ion battery thermal model. The online identification scheme can automatically identify the model parameters based on the commonly available onboard signals and update the observer for adaptive monitoring. When the internal resistance of the battery is temperature dependent, which is a more realistic situation, the least square algorithm can be augmented with non-uniform forgetting factors. The algorithm with forgetting factors can not only track the time-varying internal resistance, but also guarantee unbiased identification of the remaining constant parameters. The online parameterization also shows the capability to track the long-term variation (over cycles and days) of the internal resistance due to aging or degradation/abuse. The growth in internal resistance can be used for the SOH monitoring of the batteries. The methodology developed has been verified with simulations and is to be validated with experiments in the immediate future.

Applications, such as HEV, BEV and PHEV, usually have hundreds, or even thousands, of battery cells in series to meet their high power and energy requirements. Hence the vehicle level battery thermal management will be performed on a module basis, instead of on a cell basis. The single cell thermal model used in this paper can be scaled up to a pack model by considering cell to cell thermal interaction, and the parameterization methodology and the adaptive observer design will be investigated for the pack level model. Initial results of this pack level work can be found in [21].

IX. Acknowledgments

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