State of Charge Estimation of Lithium-ion Batteries Considering Model and Parameter Uncertainties

Zhimin Xi[1], Rong Jing[2], Xiao Guang Yang[3], and Ed Decker[4]

[1,2]*University of Michigan - Dearborn, Dearborn, MI, 48128, USA*

zxi@umich.edu
rjing@umich.edu

[3,4]*Ford Motor Company, Dearborn, MI, 48121, USA*

xyang11@ford.com
edecker6@ford.com

ABSTRACT

Up to date, model and parameter uncertainties are generally overlooked by majority of researchers in the field of battery study. As a consequence, accuracy of the SOC estimation is dominated by the model fidelity and may vary from cell-to-cell. This paper proposes a systematic framework with associated methodologies to quantify the battery model and parameter uncertainties for more effective battery SOC estimation. Such a framework is also generally applicable for estimating other battery performances of interest (e.g. capacity and power capability). There are two major benefits using the proposed framework: i) consideration of the cell-to-cell variability, and ii) accuracy improvement of the low fidelity model comparable to the high fidelity without scarifying computational efficiency. One case study is used to demonstrate the effectiveness of the proposed framework.

1. INTRODUCTION

Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEVs) and Electric Vehicles (EVs) are gaining the popularity in automotive industry. Lithium-ion (Li-ion) battery is the most promising power source for HEVs/PHEVs/EVs due to its light weight, high energy density and relatively low self-discharge compared to Ni-cad and NiMH batteries. Battery performances of interest, such as State-of-Charge (SOC), capacity and power capability, have been extensively studied due to their importance in real HEVs/PHEVs/EVs applications (Santhanagopalan & White, 2008; He et al., 2012; He et al., 2012). Battery SOC, similar to the remaining gas in the gasoline vehicles, is of particular interest and should be exactly known at any operating time. Unfortunately, the percentage of the charge remaining in the battery, namely the battery SOC, is not a directly measurable quantity and thus should be accurately estimated instead.

Coulomb counting is the most widely employed method for tracking the SOC provided that the initial SOC is known (Ng et al., 2008). Otherwise, Kalman Filter (KF) and Extended Kalman Filter (EKF) are typical methods for fast SOC estimation based on various equivalent circuit models of the Li-ion battery (Plett, 2004). Other methods in machine learning have been recently explored in the SOC estimation and/or degradation parameter (e.g., capacity) estimation (Andre et al., 2012; Lee et al., 2011; Santhanagopalan and White, 2010; Hu et al., 2012; He et al., 2013).

A common limitation in battery SOC estimation is ignorance of the battery parameter uncertainty if they are the same type and come from the same manufacturer. As a consequence, accuracy of the SOC estimation may vary from cell-to-cell. Another important limitation is unawareness of the model uncertainty which comes from the fact that no battery model can truly represent the physical system without any error in various operating conditions. Since the SOC estimation is conducted on the basis of the assumed 'perfect' battery model, any level of model uncertainty will cause biased SOC estimation regardless of the specific numeric algorithms. Up to date, the aforementioned two limitations are generally overlooked by majority of researchers in the field of battery study.

Contribution of this paper is to propose a systematic framework with associated methodologies to quantify the battery model and parameter uncertainties for more effective battery SOC estimation. Such a framework is also generally applicable for estimating other battery performances of interest (e.g. capacity and power capability).

The structure of the paper is organized as follows. Section 2 illustrates model and parameter uncertainties of the battery model. Section 3 presents a framework with associated

Xi et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

methodologies to quantify the battery model and parameter uncertainties for more effective SOC estimation. Case study is presented in Section 4 for the demonstration of the proposed framework. Finally, conclusion is made in Section 5.

2. MODEL AND PARAMETER UNCERTAINTIES

This section first presents a brief review of Li-ion battery models, and then illustrates model uncertainty and parameter uncertainty in the following two subsections, respectively.

2.1 Battery Model

Battery model can be classified into two groups: electrochemical models and equivalent circuit models. Electrochemical models are physics-based models where a set of governing non-linear differential equations are used to predict the battery internal state variables which can be further related to the typical battery performances of interest. They are generally treated as high fidelity models requiring high computational effort and thus are not desirable in real time battery SOC and State of Health (SOH) diagnosis. Equivalent circuit models are simplified physics-based models where a capacitor (or a voltage source) and resistors are used to represent the diffusion process and internal impedance of the battery cell, respectively. Compared to the electrochemical models, they can be viewed as low fidelity models with less accuracy but very high computational efficiency. Thus, majority of the Battery Management System (BMS) employs the equivalent circuit models for battery SOC and SOH diagnosis.

A discrete time state-space model (see Eq, (1)) is typically used to estimate the battery hidden states (e.g. SOC and capacity) using the KF/EFK on the basis of the equivalent circuit models.

$$\begin{cases} \mathbf{x}_{k+1}=f(\mathbf{x}_k,\mathbf{u}_k)+\mathbf{w}_k \\ \mathbf{y}_k=g(\mathbf{x}_k,\mathbf{u}_k)+\mathbf{v}_k \end{cases} \tag{1}$$

where $\mathbf{x}_k$ is the state vector at the k^{th} step; $\mathbf{u}_k$ means the input vector (e.g. current); $\mathbf{w}_k$ is the process noise; $\mathbf{y}_k$ is the output vector (e.g. terminal voltage); $\mathbf{v}_k$ is the measurement noise of the output vector; $f(\cdot)$ is the state transition function; and $g(\cdot)$ is the equivalent circuit model that relates the output vector with the input and hidden state vectors.

2.2 Model Uncertainty

When battery models are accurate and reliable, the output vector predicted from the model would be exactly the same as the true test results under various operating conditions. It is worth noting that above statement is valid when satisfying three conditions: i) no model parameter uncertainty, ii) no numerical algorithm uncertainty, and iii) no test error. However, models are generally built on the basis of many assumptions and simplifications and therefore model uncertainty may always exist because there is probably no ideal model which can predict the real physical system without any model bias.

Eq. (2) shows one specific state-space model used for the SOC estimation.

$$\begin{cases} x_{k+1} = x_k - \eta T i_k / C_n + w_k \\ y_k = OCV(x_k) - i_k R + h_k + v_k \end{cases} \tag{2}$$

where x_{k+1} is the SOC at the $(k+1)^{\text{th}}$ step; $\eta T i_k$ is the coulomb accumulation for given charging/discharging efficiency (η), current (i_k) and time accumulation T; C_n is the nominal capacity. The second equation is the equivalent circuit model which builds the functional relationship for terminal voltage y_k, OCV, internal impedance R and voltage change h_k due to the hysteresis effect. A one-state hysteresis model is further expressed in Eq. (3).

$$h_k = \exp\left(-\left|\frac{\eta_i i_{k-1}\gamma\Delta t}{C_n}\right|\right) h_{k-1} + \left(1 - \exp\left(-\left|\frac{\eta_i i_{k-1}\gamma\Delta t}{C_n}\right|\right)\right) M \tag{3}$$

where γ is a positive constant which tunes the rate of decay; and M is a polarization coefficient.

For one specific battery cell, model uncertainty is the deterministic difference between the predicted terminal voltage y_k and the true terminal voltage, which indicates the model inadequacy for representing the actual functional relationship under various battery operating conditions. In general, parameter uncertainty which will be illustrated in the next subsection is coupled with the model uncertainty and should be taken into account when characterizing the model uncertainty. Thus, model uncertainty becomes the stochastic difference between the predicted terminal voltage y_k and the true terminal voltage. For the equivalent circuit model considered above, a corrected model after introducing the model uncertainty can be defined in Eq. (4).

$$y_k = OCV(x_k) - i_k R + h_k + \delta(i_k, x_k,\ C_k) + v_k \tag{4}$$

where $\delta(\cdot)$ is the model uncertainty function which is also referred as the model bias in model validation community.

Development of an effective model uncertainty characterization approach can improve model prediction accuracy in the intended uses of the model. Such process is especially useful to improve accuracy of a low fidelity model (e.g. equivalent circuit models with high computational efficiency) comparable to a high fidelity model (e.g. electrochemical models with low computational efficiency) so that battery SOC and SOH diagnosis can be conducted more effectively.

2.3 Parameter Uncertainty

A common mistake in battery SOC and SOH diagnosis is ignorance of the fact that the battery used in laboratory test is different with others in real operation due to various sources of uncertainties (e.g. physical uncertainty) even if they are the same type and come from the same manufacturer. Physical uncertainty can be viewed as the cell-to-cell variability due to manufacturing tolerance. Correspondingly, parameter uncertainty is the realization of the physical uncertainty in the specific battery models.

According to the battery model in Eq. (3) and Eq. (4), model parameters (e.g. internal impedance R, decay factor γ, etc.) contain uncertainty due to the cell-to-cell variability and thus should be quantified appropriately. Otherwise, the battery SOC estimation may be accurate for one cell under perfect calibration condition, but not so accurate for other cells. The accuracy variability depends upon two factors: i) significance of the parameter uncertainty and ii) sensitivity of the accuracy with respect to the parameter uncertainty.

2.4 Remarks on Model and Parameter Uncertainty

In model calibration, the objective is to maximize the agreement between the model prediction and the experimental data. A common approach for simplification is to disregard the model uncertainty by maximizing the agreement between the original model prediction and the experimental data through calibration of unknown model parameters (e.g., internal impedance R, decay factor γ, etc.). It is apparent that the calibrated model parameters may not be the true values. This is acceptable in model calibration because models are treated more pragmatically to increase their predictive power for one or several specified battery cells. However, if the objective is to improve the model prediction accuracy for the population of the battery cells under various operating conditions, it is risky to directly use model calibration technique because the model prediction could be inaccurate out of the calibration domain due to incorrect calibration of the model parameters and ignorance of the model uncertainty.

3. PROPOSED FRAMEWORK FOR SOC ESTIMATION

The proposed systematic framework is shown in Fig. 1 with consideration of the model and parameter uncertainties for more effective SOC estimation. There are two major benefits using the proposed framework: i) consideration of the cell-to-cell variability and ii) accuracy improvement of the initial battery model. Basically, this framework enables user to select a low fidelity battery model with high computational efficiency without scarifying the accuracy because a corrected battery model with high accuracy can be later obtained through characterizing the model uncertainty. Furthermore, battery SOC or SOH diagnosis becomes probabilistic instead of deterministic so that confidence of the estimation is available. Following subsections elaborate each step of the framework.

3.1 Determination of Initial Battery Model

The initial battery model ideally should include major input factors which influence the output performances. For example, OCV, SOC, charge/discharge current, hysteresis and temperature are important inputs for predicting the terminal voltage accurately and thus they should be considered in the empirical model. The purpose is to have a good base model with reasonable accuracy so that model uncertainty can be more effectively quantified to improve the model prediction accuracy. Otherwise, more noise factors would be included in the quantified model uncertainty such that the corrected model prediction would provide much wider confidence intervals to account for the ignorance of the important factor. In this study, the equivalent circuit model in Eq. (2) and Eq. (3) is used without considering the temperature effect. Thus, testing is conducted in the room temperature to eliminate the noise factor from various temperature levels for the SOC estimation.

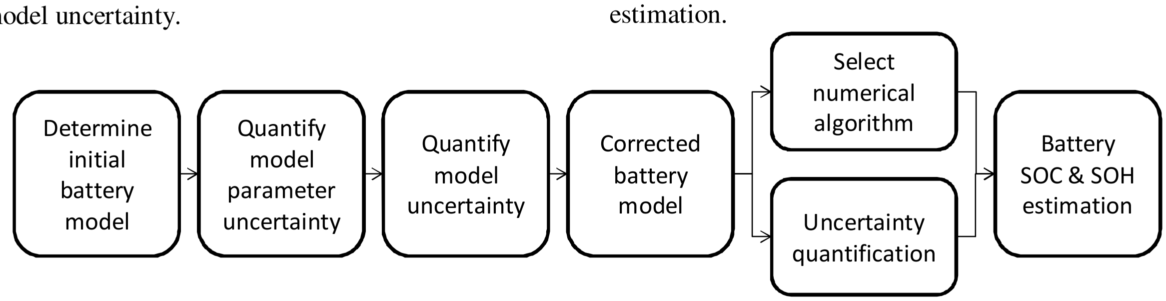


Figure 1. Flowchart of the proposed framework for battery SOC and SOH estimation

3.2 Quantification of Parameter Uncertainty

A certain number of battery cells should be determined to account for the cell-to-cell variability based on the parameter uncertainty. For example, defined pulse power capability tests of five battery cells result in five sets of model parameters after calibration of each battery cell individually. Thus, five random realizations are available for quantifying the uncertainty of each model parameter. The issue of data sufficiency needs to be addressed in this step.

Typically, random parameters can be classified into two groups: i) irreducible random parameter and ii) reducible random parameter. The irreducible random parameters are characterized using Probability Density Functions (PDFs) with sufficient information. The reducible random parameters are derived from the lack of information for describing the uncertainty. For example, parameters, i.e., the mean and the variance of the PDF, or even distribution types are uncertain unless sufficient information is collected.

This study considers parameter uncertainty as irreducible random parameter and use Maximum Likelihood Estimation (MLE) to select the optimal distribution for each model parameter. The statistics of the random parameter is represented by the statistical parameter Θ of a candidate distribution. For example, in the case of a normal distribution, the parameter is defined as $\Theta=\{\mu_\theta, \sigma_\theta\}$, which includes the mean and standard deviation. Thus, Θ is the calibration parameter and needs to be identified. The statistical model calibration using MLE is formulated as

$$\text{Maximize } L(V_i \mid \Theta) = \sum_{j=1}^{M} \log_{10}\left[f\left(v_{ij} \mid \Theta\right)\right] \tag{5}$$

where $L(\cdot)$ is the likelihood function; $f(\cdot)$ is the PDF of V_i for a given Θ; i means the i^{th} model parameter; and M is the number of available data. A candidate distribution pool, including Normal, Lognormal, Weibull, Beta, Gamma, and Uniform, is defined and the optimal distribution is determined by the maximum likelihood value among candidate distributions.

3.3 Quantification of Model Uncertainty

The objective for quantifying model uncertainty is to improve the model prediction accuracy by adding the identified model uncertainty to the original model as shown in Eq. (4). A two-step calibration procedure is proposed to accurately characterize the model uncertainty (or model bias) in various battery operating conditions.

Step 1: calibrate unknown model parameter V_i through calibration experiments as described in section 3.2;

Step 2: calibrate the model uncertainty using the statistical calibration technique at several defined battery operating conditions using the Design of Experiment (DOE) technique.

Then three steps are used to obtain the model uncertainty in various battery operating conditions with the aid of the response surface.

Step 1: construct response surfaces for the central moments (e.g., mean and standard deviation) of the model uncertainty using the moving least square method;

Step 2: calculate the central moments of the model uncertainty at any given operating condition on the basis of the response surfaces;

Step 3: approximate the distributions of the model uncertainty at any given operating condition.

Response surface of the model uncertainty plays a critical role in the process of obtaining corrected model prediction. Its accuracy mainly depends on three factors including: i) nonlinearity of the model uncertainty in various battery operating conditions; 2) amount and location of the identified model uncertainty using the DOE technique; and 3) numerical algorithm of the response surface method.

3.4 Correction of Initial Battery Model

The corrected battery model is shown in Eq. (6) by adding the identified model uncertainty to the initial battery model. Furthermore, model parameter uncertainty is characterized by optimal PDFs to account for the cell-to-cell variability. The corrected model is a statistically validated model and is expected to produce more accurate and robust SOC estimation.

$$\begin{cases} x_{k+1} = x_k - \eta T i_k / C_n + w_k \\ y_k = OCV(x_k) - i_k R + h_k + \delta(i_k, x_k, \dot{x}_k) + v_k \end{cases} \tag{6}$$

3.5 Selection of Numerical Algorithm

KF has been widely used in many applications to estimate the hidden state for the linear state-space model. As an extension, EKF applies for non-linear state-space model using the linear approximation at each estimation step. Other KF related approaches are also reported such as adaptive KF, unscented KF, etc. All KF related approaches use linearity and Gaussian noise assumptions, which could cause numerical estimation error for the non-linear model with non-Gaussian noise. In that scenario, Particle Filter (PF) (Orchard & Vachtsevanos, 2009) is more appropriate to approximate the state PDF using Bayesian approach and avoiding such assumptions. However, PF is much more computational expensive than EKF. This study employs the EKF for demonstration of the proposed framework due to its reasonable accuracy and efficiency.

3.6 Uncertainty Quantification

The objective is to estimate SOC of the battery in a statistical manner using the validated battery model and the EKF. All sources of uncertainties are considered in model parameters and identified model uncertainty/bias. Essentially, the SOC estimation becomes an Uncertainty Quantification (UQ) process to quantify the distribution of the battery SOC subject to the input uncertainties from the model parameter, model uncertainty/bias and the measurement and process noise.

A common challenge in UQ is a multi-dimensional integration to quantify probabilistic nature of system responses. Neither analytical multi-dimensional integration nor direct numerical integration is possible for large-scale engineering applications. Other than those approaches, existing approximate methods for UQ can be categorized into five groups (Youn et al., 2008): i) sampling method, ii) expansion method, iii) the most probable point (MPP)-based method, iv) response surface approximate method, and v) approximate integration method. This study uses sampling method (i.e. the Monte Carlo Simulation) for UQ.

4. CASE STUDY

This section presents a case study to demonstrate the effectiveness of the proposed framework for SOC estimation.

4.1 Background

EIG C020 battery cells are used in this case study with the nominal capacity of 20Ah. Four battery cells were connected parallel to four channels of the battery cycler (Arbin BT2000). All experiments, including static capacity test, energy efficiency test, HPPC test, OCV-SOC test and FUDS test, were conducted at the room temperature (25 ^{o}C). Capacity test results are shown in Table 1 with the mean and standard deviation equal to 19.66 Ah and 0.037 Ah, respectively. Efficiency test results are listed in Table 2 for both charge and discharge efficiency with an overall mean of 0.997. In this study, the nominal capacity (=19.66 Ah) and charge/discharge efficiency (=0.997) are treated as constant value for the SOC estimation. OCV-SOC curve is obtained as shown in Fig. 2.

Table1. Static capacity test

	Cell #1	Cell #2	Cell #3	Cell #4	Mean	STD
Capacity	19.628	19.701	19.629	19.682	19.66	0.037

Table 2. Energy efficiency test

	Cell #1	Cell #2	Cell #3	Cell #4	Mean
Discharge efficiency	0.9970	0.9978	0.9982	0.9990	0.9983
Charge efficiency	0.9900	0.9980	0.9980	0.9965	0.9956

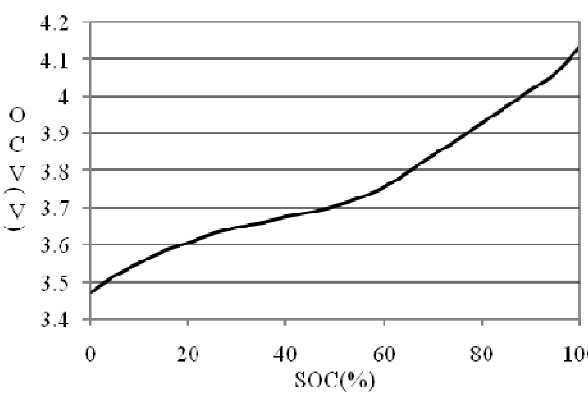


Figure 2. OCV-SOC curve

4.2 Results

Four battery cells were used to study the uncertainty of four model parameters including: i) charging impedance $R+$, ii) discharge impedance $R-$, iii) decay factor γ, and iv) polarization coefficient M. Table 3 shows that the decay factor γ presents no uncertainty and other three parameters present different level of uncertainties. For example, the standard deviation (STD) of charging impedance $R+$ is 5.2% of its mean value. Typically, we should not ignore the parameter uncertainty if the STD is more than 1% of its mean value. Hence, three model parameters were characterized as random parameters and they were assumed to follow normal distribution with identified statistical moments listed in Table 3.

Table 3. Uncertainty quantification of model parameters

Parameter	$R+$	$R-$	γ	M
Cell #1	0.0023	0.0037	1.6026	0.0172
Cell #2	0.0021	0.0037	1.6026	0.0162
Cell #3	0.0024	0.0036	1.6026	0.0171
Cell #4	0.0022	0.0035	1.6026	0.0163
Mean	0.0025	0.0036	1.6026	0.0167
STD	1.29e-4	9.57e-5	0	5.23e-4
Percentage	5.2%	2.7%	0%	3.1%

The first three battery cells were used as training data to quantify the model uncertainty. In this case study, response surface of the model uncertainty was constructed only for the 1st central moment (i.e. the mean) for simplification. FUDS test was then carried out for cell #4. Mean of the model uncertainty for the cell #4 was estimated for the FUDS test and the results are shown in Fig. 3.

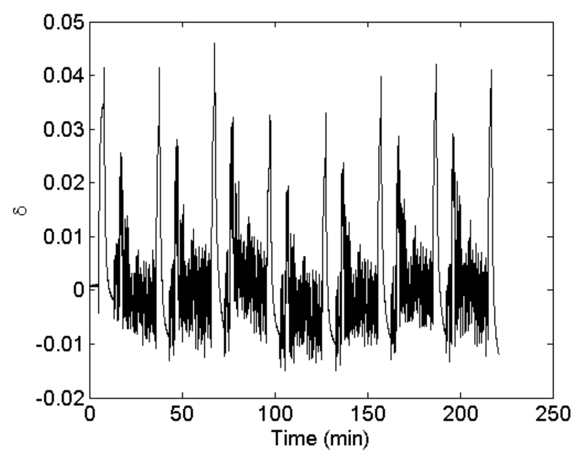
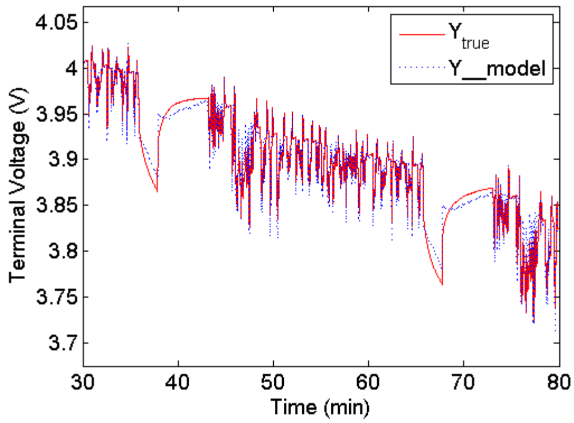
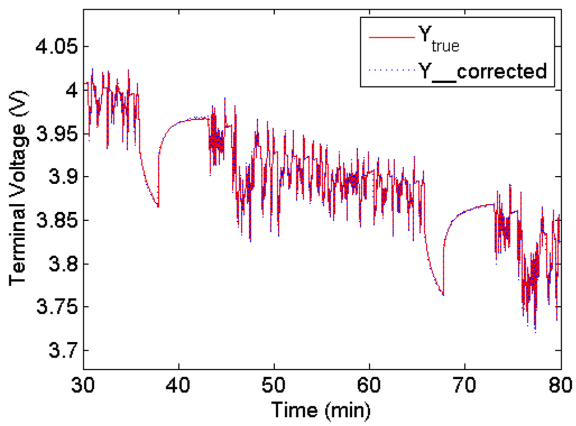


Figure 3. Mean of the model uncertainty of cell #4 for the FUDS test

According to the original battery model, estimated terminal voltage generally agrees well with actual measurement as shown in Fig. 4(a). However, the difference is observable especially during the rest period in between the FUDS cycles, which is mainly due to the model inadequacy for representing the actual physical system. Such model limitation can be overcome by considering the model uncertainty using Eq. (4). Based on the identified model uncertainty (see Fig. 3) for the FUDS test, the corrected terminal voltage agrees much better than the original model as shown in Fig. 4(b).



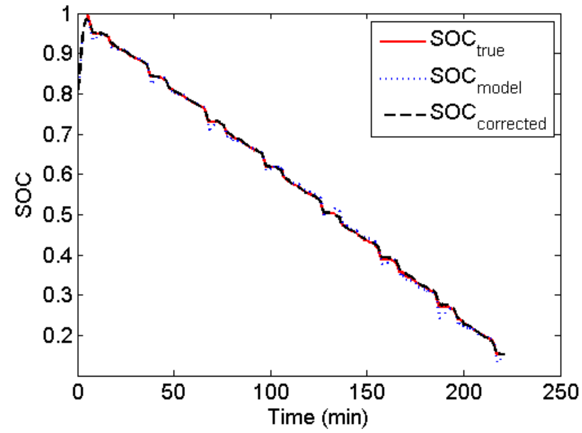
(a) Without model uncertainty



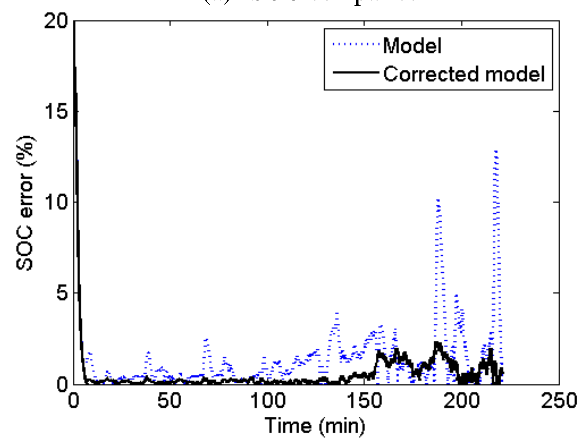
(b) With model uncertainty

Figure 4. Comparison of terminal voltage for the original model and corrected model

SOC estimation was conducted using both original battery model and corrected model with consideration of the model uncertainty. The battery cell #4 was first fully charged with 100% of SOC; and then one FUDS cycle was applied and followed by a constant discharge current and a rest period. Such process was repeated till the SOC reached 10%. SOC calculated using the coulomb counting was treated as the reference value. EKF was used for SOC estimation for both battery models: i) original model without consideration of model uncertainty, and ii) corrected model with consideration of model uncertainty. The initial guess of SOC was set to 80% using the EKF for both models. Results are shown in Fig. 5 with clear indication that accuracy of SOC estimation can be significantly improved by considering the model uncertainty appropriately. In particular, the maximum percentage error (excluding the initial error) of the SOC estimation reaches 14% using the original model, whereas, the error is well below 5% if the model uncertainty is considered.



(a) SOC comparison



(b) Percentage error of SOC

Figure 5. SOC estimation with and without consideration of the model uncertainty

5. CONCLUSION

A novel framework was proposed for quantifying model and parameter uncertainties for battery SOC and SOH diagnosis. Various uncertainty sources should be systematically addressed in order to have reliable battery management system and accurate SOC and SOH diagnosis in real HEV/PHEV/EV applications. In summary, four types of uncertainty play a key role for reliable estimation of the battery performances of interest and they are listed as: i) measurement uncertainty, ii) algorithm uncertainty, iii) model parameter uncertainty, and iv) model uncertainty. Measurement uncertainty includes current and voltage measurement error and has been well considered by most researchers. Algorithm uncertainty focuses on accuracy of numerical algorithms for estimating the battery hidden state. This field of research evolves gradually and typical algorithms include Kalman filter, extended Kalman filter and particle filter. A trade-off between numerical accuracy and efficiency should be considered depending upon specific applications. Model parameter uncertainty is not well considered up to date in the field of battery study. However, as massive products in the foreseeable future, their physical uncertainty due to the manufacturing tolerance should be well addressed. Ignorance of model parameter uncertainty makes unreliable battery SOC and SOH diagnosis. Finally, model uncertainty dominates the accuracy level of battery SOC and SOH diagnosis. Different battery models represent different levels of fidelity comparing to the actual physical system. However, majority of the research focuses on the model development itself. This paper turns an eye on quantifying the model uncertainty so that the low fidelity model can possess the accuracy of high fidelity model without scarifying the computational efficiency. Preliminary case study of the SOC estimation demonstrated the effectiveness of the proposed framework.

ACKNOWLEDGEMENT

Research was supported by Ford Motor Company and we appreciate Professor Chris Mi and Mr. Rui Xiong for sharing part of their test data and having valuable discussion with us.

REFERENCES

Andre, D., Nuhic, A., Guth, T.S., and Sauer, D.U., (2012), Comparative study of a structured neural network and an extended Kalman filter for state of health deternimation of lithium-ion batteries in hybrid electric vehicles. *Engineering Applications of Artificial Intelligence*, v26, n 3, p951-961.

He, H., Xiong, R., Guo, H., and Li, S. (2012), Comparision study on the battery models used for the energy management of batteries in electric vehicles. *Energy Conversion and Management*, v64, p113-121.

He, W., Williard, N., Chen, C., and Pecht, M., (2012), State of charge estimation for electric vehicle batteries under an adaptive filtering framework. *Prognostics & System Health Management Conference*, Beijing, China, 2012.

He Y., Liu X.T., Zhang C.B., Chen Z.H., 2013, A new model for State-of-Charge (SOC) estimation for high-power Li-ion batteries. *Applied Energy*, v101, p808–814.

Hu C., Youn B.D., and Chung J., (2012), A multiscale framework with extended Kalman filter for lithium-ion battery SOC and capacity estimation. *Applied Energy*, v92, p694–704.

Lee S., Kim J., Lee J., and Cho B.H., (2011), Discrimination of Li-ion batteries based on Hamming network using discharging–charging voltage pattern recognition for improved state-of-charge estimation. *Journal of Power Sources*, v196, n4, p2227–2240.

Orchard, M.E., and Vachtsevanos, G.J., (2009), A particle-filtering approach for on-line fault diagnosis and failure prognosis. Transctions of the Institute of Measurement and Control, v31, n3/4, p221-246.

Plett, G.L., (2004), Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs Part 2. Modeling and identification. *Journal of Power Sources*, v134, n2, p262-276.

Plett, G.L., (2004), Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs Part 3. State and parameter estimation. *Journal of Power Sources*, v134, n 2, p277–292.

Ng, K.S., Moo, C.S., Chen, Y.P., and Hsieh, Y.C., (2008), Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries. *Applied Energy*, v86, p1506-1511.

Santhanagopalan, S., and White, R.E., (2008), State of charge estimation for electrical vehicle batteries. *IEEE, 17th International Conference on Control Applications, Part of 2008 IEEE Multi-conference on System and Control*, San Antonio, Texas, USA, September 3-5, 2008.

Santhanagopalan S., and White R.E., (2010), State of charge estimation using an unscented filter for high power lithium ion cells. *International Journal of Energy Research*, v34, n2, p152–163.

Youn, B.D., Xi, Z., and Wang, P., (2008), Eigenvector Dimension-Reduction (EDR) method for sensitivity-free probability analysis. *Structural and Multidisciplinary Optimization*, v37, p13-28.

BIOGRAPHIES

Zhimin Xi is an Assistant Professor in the Department of Industrial and Manufacturing Systems Engineering at University of Michigan – Dearborn. He received his B.S. and M.S. degree in Mechanical Engineering from Beijing University of Science and Technology in 2001 and 2004, respectively. He received his Ph.D. in Reliability Engineering from University of Maryland – College Park in 2010. He has over 30 publications in prestigious journals and international conferences. He is the two-time winners of the Best Paper Award from ASME – Design Automation Conference in 2008 and 2013, respectively. His research interests are reliability engineering, prognostics and health management, and energy storage device.

Rong Jing is a graduate student in the Department of Industrial and Manufacturing Systems Engineering at University of Michigan – Dearborn. She received her B.S. degree in Industrial Engineering from Xi'an Jiaotong University in 2012. She is the one-time winner of the Best Paper Award from ASME – Design Automation Conference in 2013. Her research interests are diagnostics, prognostics and health management.

Xiao Guang Yang received his Ph.D. from Zhejiang University in 1995, and then worked at University of Hawaii and Penn State Univ. In 2005, Dr. Yang joined Ford for HEV programs. He is a Technical Expert and Supervisor in the Energy Storage and Materials Research Department. He currently focuses on battery modeling, benchmark, and hybrid vehicle battery system simulation and validation. He is a member of USABC (Advanced Battery Consortium Technical Committee). He has 50 journal publications, 7 Ford Technical Reports, 3 US patents and 3 US patent applications.

Ed Decker is a battery cell integration and product development engineer for the Ford Motor Company. He has two degrees from the University of California (Biology and Chemical Engineering). He has worked in battery development since 1984 and spent 16 years working on batteries for the consumer electronic market. He joined Ford Motor Company in 2010 and is currently working on developing batteries for BEV and PHEV applications.