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Battery State of Charge Estimation Based on a Combined Model of Extended Kalman Filter and Neural Networks

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Abstract—This paper presents our research in battery State of Charge (SOC) estimation for intelligent battery management. Our research focus is to investigate online dynamic SOC estimation using a combination of Kalman filtering and a neural network. First, we developed a method to model battery hysteresis effects using Extended Kalman Filter (EKF). Secondly, we designed a SOC estimation model, NN-EKF model, that incorporates the estimation made by the EKF into a neural network. The proposed methods have been evaluated using real data acquired from two different batteries, a lithium-ion battery U1-12XP and a NiMH battery with 1.2V and 3.4 Ah. Our experiments show that our EKF method developed to model battery hysteresis based on separated charge and discharge Open Circuit Voltage (OCV) curves gave the top performances in estimating SOC when compared with other advanced methods. Secondly, the NN-EKF model for SOC estimation gave the best SOC estimation with and without temperature data.

Keywords- battery SOC; Kalman filtering; neural networks, intelligent battery management

I. INTRODUCTION

In response to the ever-increasing concerns on environmental protection and energy conservation, research and development of advanced technologies for hybrid electric vehicles and electric vehicles system (HEVs & EVs) are being actively conducted. Among those HEVs & EVs technologies, battery technology is the key to commercialization and popularization of HEVs & EVs.

To ensure that the battery will perform as expected, a battery management system (BMS) should be designed to monitor and control battery energy level. A BMS is generally defined as any electronic device that manages a rechargeable battery (cell or battery pack). The main objectives of the BMS are monitor, computation, communication, protection and optimization [4, 13].

Estimation of State of Charge (SOC) is one of the most important functions in battery management. SOC is defined as the percentage of the releasable capacity relative to the battery rated capacity. Accurate estimation of the SOC is important to battery performance optimization including extending battery lifetime and preventing permanent damage to batteries. The importance of SOC Determination in battery management is summarized as follows [5, 6]:

- For State of Health (SOH) Estimation applications, since there is no absolute definition of the SOH, SOC becomes an important indicator to estimate SOH.
- For Cell Protection, BMS determines whether the battery is over-charged or over-discharged based on the value of SOC, thereby to control the charge and discharge current.
- For Cell Equalization applications, it is only necessary to know the SOC of any cell relative to the other cells in the battery chain. BMS deals with unequal SOC by only charging the cell with lower SOC.

Accurate estimation of battery SOC is complicated due to the fact that SOC of battery depends on many factors such as current, temperature, battery capacitance and internal resistance, battery age, cut-off voltage, and service history. The SOC of a battery is a non-linear function of all these parameters. A variety of techniques has been proposed to measure or monitor the SOC of a battery cell or a battery pack [5-12]. The main SOC estimation techniques include the discharge test, the coulomb counting, open-circuit voltage measures, inherent resistance measures and the intelligent SOC estimation methods.

Computational intelligence techniques such as neural network, fuzzy logic and Kalman filter have been investigated for BMS research. They offer several advantages when compared with other techniques such as simple current and voltages measurements. Additionally, the intelligent techniques are easy to implement in digital electronic systems, and they can respond to the time-invariant behavior of batteries by their self-learning ability. In this paper, we focus on neural network and Extended Kalman Filter (EKF) based techniques for battery modeling.

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First, we present a battery hysteresis modeling algorithm based on EKF for estimating battery SOC. The proposed SOC estimation method defers from the classic EKF methods [6, 7] in the Open Circuit Voltage (OCV) curve used in building battery model for SOC estimation. Secondly, we propose a combined mode, NN-EKF, developed for dynamic online SOC estimation. We evaluated both methods through experiments conducted on real battery data acquired from two different types of batteries, a lithium-ion battery with 12V and 40 Ah, and a NiMH battery with 1.2V and 3.4Ah.

The experimental results show that the proposed EKF based SOC estimation trained using a split OCV charge and discharge method gave superior performances for both types of batteries in comparison with other EKF methods. The NN-EKF model gave the top performances in SOC estimation in various battery operating environments.

The paper is organized as follows. Section II gives an overview of major technologies for SOC estimation. Section III presents our dynamic battery modeling based on EKF, with particular emphases on addressing the hysteresis problem. Section IV presents the neural network combined with EKF for SOC estimation. Section V presents experiments designed to evaluate the effectiveness of the proposed EKF method for battery hysteresis modeling and the NN-EKF model for online SOC estimation. The conclusions are presented in Section VI.

II. OVERVIEW OF SOC ESTIMATION APPROACHES

Accurate estimation of battery SOC is a key technology in a BMS. Many techniques have been developed for estimating the SOC of a battery. Some are specific to particular cell chemistries, and others depend on measuring the battery parameters that depend on the state of charge. In this section we give a brief overview of popular SOC estimation methods [5, 13], and discuss their pros and cons.

A. Discharge Test

Discharge test is the most reliable method for determining the SOC of a battery. But such a test, which usually request a constant discharge current, is too time consuming and inflexible for most applications. Discharge test is not suitable for a running vehicle since the charge/ discharge current is varying during the vehicle running.

B. Open-circuit voltage SOC Estimation

Voltage based SOC estimation uses the open circuit voltage (OCV) of the battery cell as the basis for calculating SOC or the remaining battery capacity. There is a corresponding curve between the open circuit voltage and SOC for each battery. However, this method requires battery to rest for a long time in order to obtain stable voltage. Furthermore, OCV curve is sensitive to different discharge rates and temperature. Therefore this method is effective for measuring SOC only at the initial stage and end stage.

C. Current Based SOC Estimation - (Coulomb Counting)

The most common technique for calculating battery SOC is Coulomb counting, also known as Ampere hour counting, which is calculated as follows:

$$SOC(t) = SOC_{init} - \int_0^t \frac{i(t)}{C_n} dt$$

where $i(\mathrm{t})$ is the measured input current at time t and C_n cell nominal capacity.

Coulomb counting depends on the current flowing from the battery into external circuits. It does not take account of self discharge currents or the Coulombic efficiency of the battery.

The initial SOC of the battery is hard to determine at the start of the driving. Although we can get SOC from record of BMS or open circuit voltage look-up table, the accuracy is hard to guarantee. Furthermore, the SOC calculations rely solely on the measurement of current without taking into account the measurement noise. Such error will accumulate over time.

D. Kalman Filtering

Kalman filtering is method to estimate the inner states of any dynamic process in a way that minimizes the mean of the squared error. Its purpose is to obtain accurate information out of inaccurate data [14]. For battery SOC estimation, its input usually consists of the current, temperature, internal resistance of the battery, and the output of the system normally is voltage.

Kalman filtering can be designed to strip unwanted noise out of a stream of data. It operates by predicting the new state and its uncertainty, then correcting this with a new measurement. With the Kalman Filtering the accuracy of the battery SOC estimation model can be improved and accuracies of better than 1% are claimed for such systems.

Kalman filtering is suitable for SOC determination of HEV in which battery current is volatile. However, it has high requirements on the battery modeling and the computing ability.

E. Neural Network

As an intelligent technology, artificial neural network's strong self-learning and adaptive ability make it good at association, generalization, analogy and extension. And this is very suitable for the research of complex nonlinear system model.

Also, the classic methods of SOC estimation usually rely on the special concrete models, which differ in different battery systems and are only utilized for offline test. Comparatively, neural network (NN) can be utilized for all battery systems without knowledge of cell internal structure, so long as the net training data is available. In addition, neural network is capable of estimating SOC when the initial SOC is unknown.

A summary of above discussion is presented in Table 1. Our research focus is to investigate online dynamic SOC estimation using a combination of Kalman filtering and a neural network.

TABLE 1 SUMMARY OF SOC ESTIMATION TECHNIQUES

Technique	Field of application	Advantages	Drawbacks
Discharge test	All battery systems	Easy and accurate	Offline, time intensive, loss of energy, modifies the battery state
Voltage Based SOC Estimation	Lead, Lithium, Zn	Easy	Long rest time, offline
Coulomb Counting	All battery systems	Online, easy	Needs re-calibration points, Consider battery loss
Kalman Filtering	All battery systems	Online, Dynamic	Computationally intensive, Needs a suitable battery model
Neural Networks	All battery systems	Online	Need training data of a similar battery

III. ESTIMATION OF SOC USING EXTENDED KALMAN FILTER

A Kalman filter comprises a set of recursive equations that are being repeatedly evaluated and updated as the system operates. For the battery management application, we need to find the fitting equations by modeling the battery physical characteristic. In this section, we will first give a brief introduction to extended Kalman filtering (EKF) followed by the description of our battery SOC estimation method based on the EKF.

A. Extended Kalman Filtering

In order to use EKF methods for battery SOC estimation, we model a cell in a discrete-time state-space form. Specifically, we model the nonlinear battery system by a state equation and an output equation below:

$$x_{k+1} = f(x_k\,, u_k) + w_k \tag{1}$$

$$y_k = g(x_k\,, u_k) + v_k \tag{2}$$

where x_k is the system state vector at discrete-time index k, vector u_k is the measured system input at time k and w_k is unmeasured "process noise" that affects the system state. The output of the system is y_k and v_k is measurement noise. $f(\cdot\,,\cdot)$ and $g(\cdot\,,\cdot)$ are (possibly nonlinear) functions, determined by the particular cell model used.

At each time step, $f(x_k\,, u_k)$ and $g(x_k\,, u_k)$ are linearized by a first-order Taylor-series expansion. The model can be rewrite as:

$$x_{k+1} = A_k x_k + B_k u_k + w_k \tag{3}$$

$$y_k = C_k x_k + D_k u_k + v_k \tag{4}$$

where,

$$A_k = \frac{d[f(x_k\,,u_k)]}{d[x_k]}\bigg|_{x_k\,,u_k}\,, \quad B_k = \frac{d[f(x_k\,,u_k)]}{d[u_k]}\bigg|_{x_k\,,u_k}$$

$$C_k = \frac{d[g(x_k\,,u_k)]}{d[x_k]}\bigg|_{x_k\,,u_k}\,, \quad D_k = \frac{d[g(x_k\,,u_k)]}{d[u_k]}\bigg|_{x_k\,,u_k}$$

B. Battery model

We model the discrete state and output equations of the battery as follows [7].

$$SOC_{k+1} = SOC_k - \left(\frac{\eta_{\_i}\Delta t}{C_n}\right) i_k + w_k$$

$$V_k = OCV(SOC_k) - Ri_k - sgn_k M + v_k$$

where $SOC_k = x_k$ is an inner state of the battery system. i_k is the measured input current ($i_k > 0$ during the discharge stage and $i_k < 0$ during the charge stage). $V_k = y_k$ is the output voltage of the system. $\eta_{\_i}$ is the coulomb efficiency, which is related to charge or discharge current. Δt is the time interval $t_{k+1} - t_k$ and C_n presents the cell nominal capacity. w_k and v_k are zero-mean white Gaussian stochastic processes of covariance matrices Σ_w and Σ_v respectively. R represents the internal resistance In order to have more accurate SOC estimation, hysteresis effect modeled by $sgn_k M$ is added to the output equation.

In the output function, OCV is a function of SOC, and different OCV may have different sgn_k .

Terminal voltage hysteresis has serious consequences in predicting SOC. The battery hysteresis effect can be observed by comparing the charge/discharge curves versus SOC [4, 8]. In Fig. 4, we show the hysteresis effect of a lithium-ion battery U1-12XP (see next section for more detail) during charge and discharge period. In general, it has been observed that following a discharge, the battery voltage always relaxes to a value less than the true OCV; and following a charge, the battery voltage always relaxes to a value greater than the true OCV [4]. We generated OCV_Charge and OCV_Discharge curves from laboratory data which acquired from battery charge and discharge period separately. The OCV_Mean curve was calculated as follows:

$$OCV\_Mean = (OCV\_Charge + OCV\_Discharge)/2$$

We use the following procedure to identify the unknown parameters $\theta^{\mathrm{T}} = [R^+, R^-, M]$, where R^+ is the resistant during the charging and R^- is the one during the discharging. M denotes the battery hysteresis effect, which measures the difference between the two legs of the charge/discharge curve.

We first form the vector:

$$\mathrm{V}=[V_1 - OCV(SOC_1), V_2 - OCV(SOC_2), \dots\dots, V_N - OCV(SOC_N)]^{\mathrm{T}}$$

and the matrix

$$H = [h_1, h_2, h_3, \dots, h_N]^{\mathrm{T}},$$

where N is the number of training data samples described below.

The rows of H are

$$h_j = [i_j^+, i_j^-, sgn_j].$$

Since $V = H\theta$, we can obtain the parameters using the known matrices V and H as $\theta = (H^T H)^{-1} H^T V$ based on the separate OCV_Charge and OCV_Discharge curves, and the OCV_Mean curve.

Based on the mathematical forms of the battery model presented above, the computational steps of the EKF at each measurement interval k are summarized as follows.

Step 1. Predict a priori state SOC_k^- at time k:

$$SOC_k^- = SOC_{k-1}^+ - \left(\frac{\eta\_i \Delta t}{C_n}\right) i_{k-1}$$

Step 2. Predict a priori error covariance P_k^- at time k :

$$P_k^- = P_{k-1}^+ + \Sigma_w$$

Step 3. Compute the Kalman gain, *Kg*:

$$Kg_k = P_k^- * C_k / [C_k * P_k^- * C_k + \Sigma_v]$$

$$\left(C_k = \frac{d[OCV(SOC_k)]}{d[SOC_k]} \bigg|_{SOC_k = SOC_k^-} \right)$$

Step 4. Update state estimation based on observed voltage V_k' :

$$SOC_k^+ = SOC_k^- + Kg_k * [V_k' - V_k];$$

$$(V_k = OCV(SOC_k^-) - Ri_{k-1} - sgn_k M)$$

Step 5. Error covariance P_k^- update to P_k^+ for next time step:

$$P_k^+ = (1 - Kg_k * C_k) P_k^-$$

IV. SOC ESTIMATION USING A NEURAL NETWORK COMBINED WITH EKF MODEL (NN-EKF)

In this section we discuss the NN-EKF model designed for SOC estimation. Most important parameters that characterize battery states are voltage, current and temperature. Because of the hysteresis property of the battery, we also incorporate the past state of the battery into the neural network input. Thus NN-EKF has the following five parameters {*I(k), V(k), ΔI(k), ΔV(k), T(k), SOC(k-1)*}, where *I*, *V* and *T* represents current, voltage and temperature respectively, and *ΔI(k)= I(k)-I(k-1)), ΔV(k) = (V(k)-V(k-1)),* and *SOC(k-1)* is the estimate of SOC at k-1 by EKF. The output of neural network is *SOC(k).*

The novelty of this model is to incorporate EKF to make the neural network adapt to a dynamic environment. The *SOC(k-1)* generated by the EKF model that takes into the consideration of battery hysteresis and measurement noise.

Figure 1 illustrates the components and data flow in the proposed NN-EKF model.

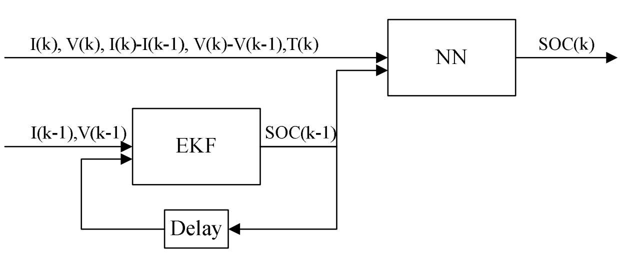


Figure 1. The scheme of NN-EKF model

V. EXPERIMENT

In this section, we present the experiments designed to evaluate the capability and the accuracy of the proposed EKF and NN-EKF model for battery SOC estimation. Two sets of data were used in our experiments. The first set of data was acquired from a lithium-ion battery U1-12XP manufactured by Valence. The battery has a nominal capacity of 40 Ah and a nominal voltage of 12V. The second set of data was acquired from a NiMH battery, MH-AAA 1000, which has 1.2V and 3.4Ah. This set of data includes the temperature data of the battery during the operation.

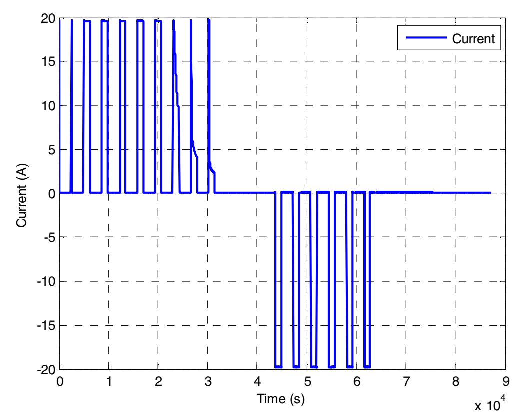
Two sets of evaluation are presented here. First we evaluate the proposed EKF method that models the battery hysteresis based on different OCV curves. Then we evaluate the NN-EKF model by comparing the experiment results generated by NN-EKF and the EKF model.

A. Cell testing for model fitting

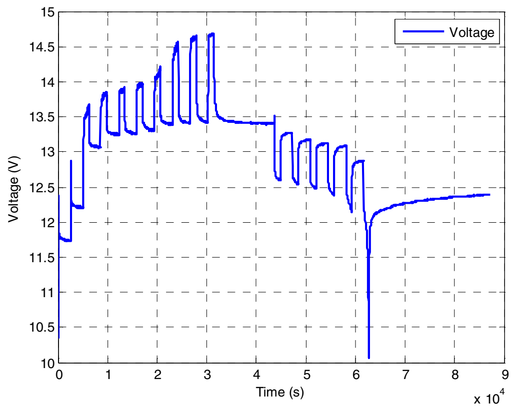
Initial parameters required for the battery model are determined from experimental data. In order to compare the abilities of the proposed models to capture a cell's dynamics, we gathered data from two batteries with different cell test cycles.

The first battery experiment data were acquired from a lithium-ion battery U1-12XP with a nominal capacity of 40 Ah and a nominal voltage of 12V. The time interval is 1s. During the experiment, we used XDC 600-10 as power supply and DSPACE to record the data from sensors at room temperature.

The cell test comprised of a sequence of constant-current charge pulses and rests followed by a sequence of constant-current discharge pulses and rests. The cell was fully discharged before the experiment began. The current and voltage profiles in this experiment are shown in Fig. 2(a) and (b). The reference SOC profile calculated from coulomb counting method is shown in Fig. 2(c).



(a)



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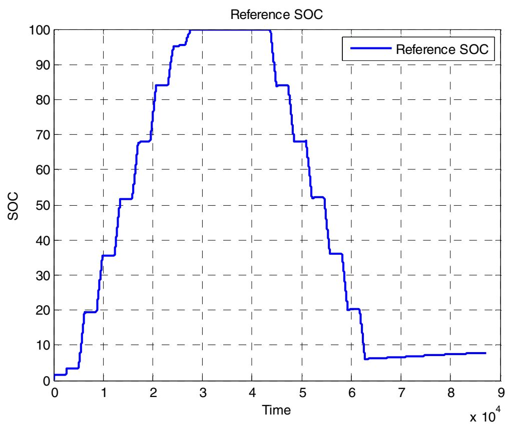
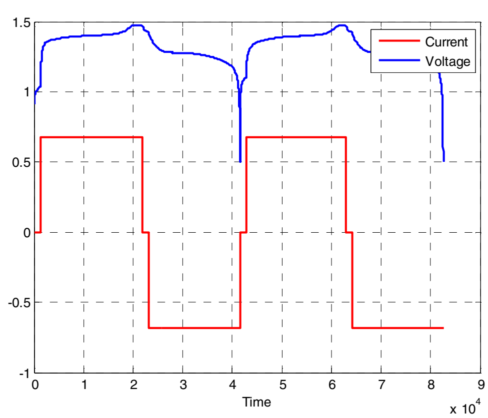


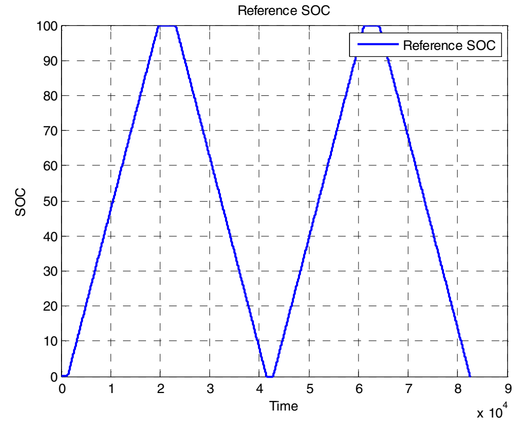
(c)

Figure 2. (a) Test current, (b) Test voltage and (c) Reference SOC

The second battery data were acquired from a NiMH battery, MH-AAA 1000, which has 1.2V and 3.4Ah. The cell test comprised of two cycles of continued constant-current charge and continued constant-current discharge. The cell was fully discharged before the experiment began. The current and voltage profiles for this test are shown in Fig. 3(a) and reference SOC profile is shown in Fig. 3(b). Reference SOC is calculated by coulomb counting method. Data were sampled at 10 second intervals.



(a)



(b)

Figure 3. (a)Voltage and Current of the cycle (b)Reference SOC of the cycle

Because the ground truth of SOC can't be measured directly, the performance of a battery model often measured by two metrics, one is based on voltage and the other on reference SOC [4]. One goal of battery modeling is to make the cell model voltage output resemble the cell terminal voltage as closely as possible at all times when the cell model input is the cell current. Therefore model performance can be measured by the root-mean-squared estimation error (RMSE) between cell terminal voltage and the model voltage output. Second measure is to calculate the RMSE between the SOC generated by the battery model and the SOC generated by coulomb counting over the portions of SOC between 5 and 95%. Model error outside this SOC range was not considered since many applications such as the HEV have operation range around 10–90% SOC.

B. OCV curves and hysteresis

As we discussed above the hysteresis effect has serious consequences in the accurate estimation of SOC. We illustrate the hysteresis effect by showing the OCV_Charge/ OCV_Discharge curves at the C/2 rate in the room temperature for the lithium-ion battery in Fig. 4(a), and the plot of hysteresis voltage versus SOC in Fig. 4(b).

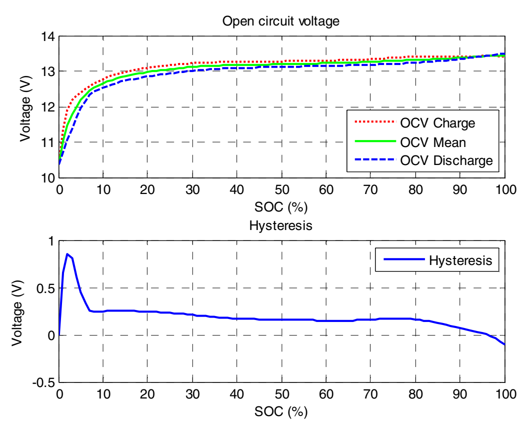


Figure 4. Open circuit voltage for U1-12XP (a) Hysteresis discharge/charge curves and (b) the hysteresis voltage.

For the NiMH battery, the hysteresis effect is shown by the OCV_Charge/OCV_Discharge curves at the C/5 rate in room temperature in Fig. 5(a), and the plot of the hysteresis voltage versus SOC in Fig. 5(b). Using the same method as above, for MH-AAA 1000, the OCV_Mean curve is shown as the green line.

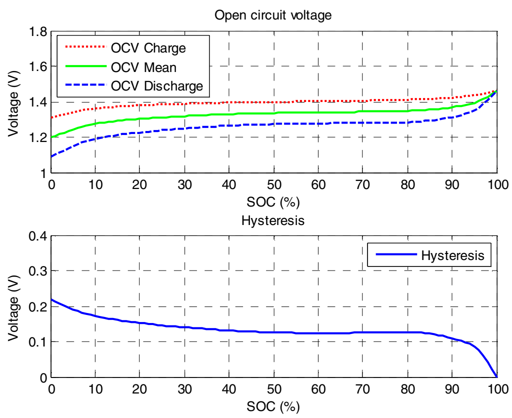


Figure 5. Open circuit voltage for MH-AAA 1000 (a) Hysteresis discharge/charge curves and (b) the hysteresis voltage.

C. *Experiment results on U1-12XP*

To compare the impact of battery hysteresis on the accuracy of SOC estimation in the model, we conducted 4 different experiments described below, each trained EKF parameters by using a different set of OCV curves.

Method 1. Use only OCV_Charge curve to get the $OCV(SOC_k)$ function and fit the whole procedure

$$OCV(SOC_k) = OCV\_Charge(SOC_k),$$

$$sgn_k = \begin{cases} 1, & when\ i_k > \varepsilon \\ 0, & when\ i_k < -\varepsilon \\ sgn_{k-1}, & when |i_k| \le \varepsilon \end{cases}$$

Method 2. Use only OCV_Discharge curve to get the $OCV(SOC_k)$ function and fit the whole procedure

$$OCV(SOC_k) = OCV\_Discharge(SOC_k),$$

$$sgn_k = \begin{cases} 0, & when\ i_k > \varepsilon \\ -1, & when\ i_k < -\varepsilon \\ sgn_{k-1}, & when |i_k| \le \varepsilon \end{cases}$$

Method 3. Use only OCV_Mean curve to get the $OCV(SOC_k)$ function and fit the whole procedure

$$OCV(SOC_k) = OCV\_Mean(SOC_k),$$

$$sgn_k = \begin{cases} 1/2, & when\ i_k > \varepsilon \\ -1/2, & when\ i_k < -\varepsilon \\ sgn_{k-1}, & when |i_k| \le \varepsilon \end{cases}$$

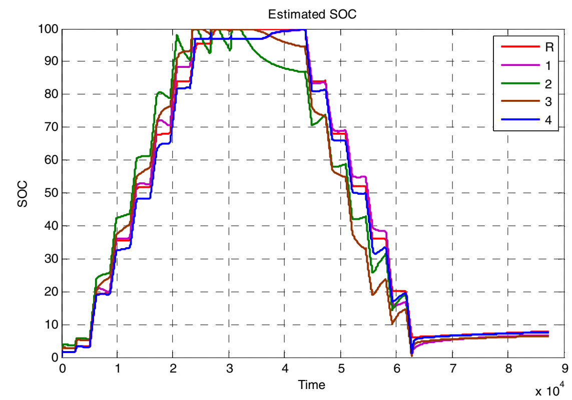
Method 4. Split charge and discharge stages with OCV_ Charge curve and OCV_Discharge curve respectively. Find the $OCV(SOC_k)$ function for the charge and discharge stage, and set

$$OCV(SOC_k) = \begin{cases} OCV\_Discharge(SOC_k), & when\ i_k > \varepsilon \\ OCV\_Charge(SOC_k), & when\ i_k < -\varepsilon \\ OCV(SOC_{k-1}), & when |i_k| \le \varepsilon \end{cases}$$

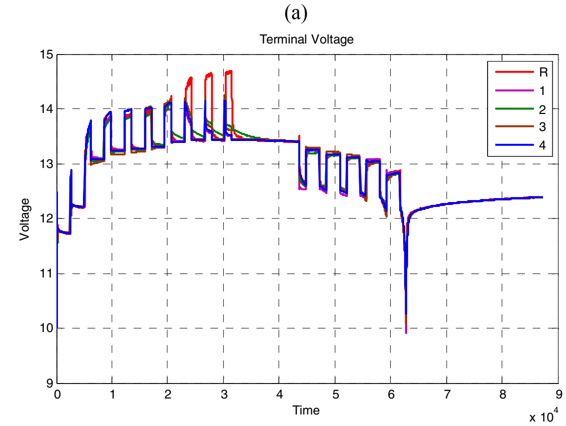
$$sgn_k = 0\ .$$

In each experiment we calculate the estimated SOC and terminal voltage using the respective $OCV(SOC_k)$ function and sgn_k value. The SOC comparison of these four different methods is shown in Fig. 6(a), and the comparison of measured and estimated terminal voltages is in Fig. 6(b). The RMSE of these test shown in Fig.6 are listed in Table 2.

The red line in the Fig. 6(a) is the reference SOC value comes from coulomb counting method for cell test. The reference voltage curve in Fig. 6(b) is measured voltage of the battery during the cell test.



(a)



(b)

Figure 6. (a) Estimated SOC for each experiments (b) Terminal Voltage for each experiments

TABLE 2 THE SOC RMS ERROR AND VOLTAGE RMS ERROR

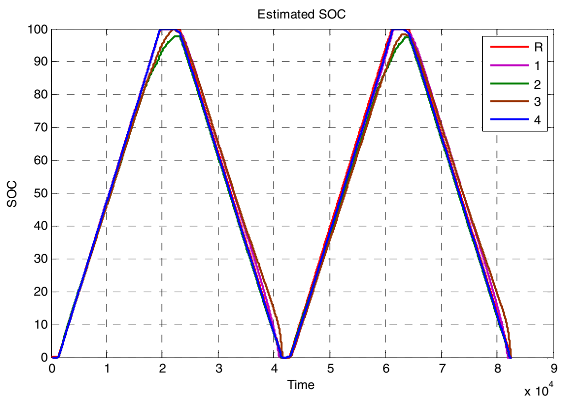
Method	Description	SOC (%) Root Mean Square Error	Voltage (V) Root Mean Square Error
1	Charge OCV curve	2.2229	0.1971
2	Discharge OCV curve	7.0817	0.1667
3	Mean OCV curve	5.2192	0.1768
4	Split OCV curve	2.0428	0.1903

By comparing both SOC and voltage errors we can see the best result is method 4: splitting the charge stage and discharge stage with their respective OCV curves being fitted to the battery model to estimate the SOC.

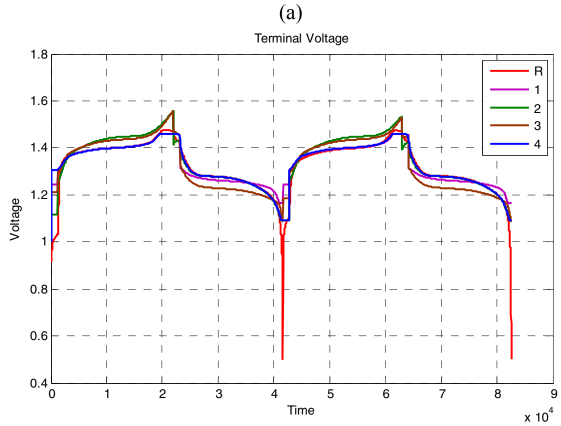
D. Experiment Results on MH-AAA 1000

To validate the proposed battery hysteresis model, we implement the battery model on the data acquire from a NiMH battery, MH-AAA 1000. The same four methods were used in the experiment.

The estimated SOC curves are shown in Fig. 7(a), and terminal voltages for each experiment are illustrated in Fig. 7(b). The RMSE of each test is listed in Table 3. As before, the red line in the Fig. 7 (a) is the reference SOC value comes from coulomb counting method for cell test. The reference voltage curve is measured voltage of the battery during the cell test in Fig. 7 (b).



(a)



(b)

Figure 7. (a) Estimated SOC for each experiments (b) Terminal Voltage for each experiments

TABLE 3 THE SOC RMS ERROR AND VOLTAGE RMS ERROR

Method	Description	SOC (%) Root Mean Square Error	Voltage (V) Root Mean Square Error
1	Charge OCV curve	2.0212	0.0539
2	Discharge OCV curve	2.6408	0.0418
3	Mean OCV curve	3.4800	0.0555
4	Split OCV curve	0.8716	0.0472

Method 4 still gives us the best performance with the proposed battery hysteresis model. The SOC estimation error is less than 1%.

E. Neural Networks Combining EKF model Experiments

In the neural network experiment part, we first try neural network SOC estimation without taking the SOC results from EKF method as inputs. In this situation, we only take I(k), V(k), ΔI(k), ΔV(k), T(k) as input variables to neural network (For U1-12XP data, since T(k) is not available, we only have the other four input variables). And the neural network has one hidden layer with 15 nodes. We split the whole data as training set and blind test set with 2:1 ratio, and the neural networks are training by BP learning method. The test performances are presented in the Table 4:

TABLE 4 THE PERFORMANCE OF NEURAL NETWORK WITHOUT SOC ESTIMATION FROM EKF AS INPUT

Data	NN SOC Root Mean Square Error (%)
U1-12XP data	5.02
MH-AAA 1000 data	3.91

By comparing with Table 2 and 3, we can see the performances of this kind of neural network are not good as the EKF method for SOC estimation.

Then we use the SOC estimation result from 4 different EKF methods as the input and design 4 neural networks combining with EKF method (NN-EKF) respectively. We still split the whole data as training set and blind test set with 2:1 ratio. The test performance on U1-12XP data are in the Table 5. We can see the significant improvement for SOC estimation by comparing to the NN without taking the SOC from EKF. The best performance of NN-EKF (Method 4) can make the SOC error less than 1%.

TABLE 5 THE PERFORMANCE OF NEURAL NETWORK COMBINING WITH EKF METHOD (NN-EKF) ON U1-12XP DATA

Method	Description	NN-EKF SOC (%) Root Mean Square Error	EKF SOC(%) Root Mean Square Error
1	Charge OCV curve	1.09	2.2229
2	Discharge OCV curve	3.9	7.0817
3	Mean OCV curve	1.94	5.2192
4	Split OCV curve	0.89	2.0428

The SOC comparison of NN-EKF and reference method is shown in Fig. 8

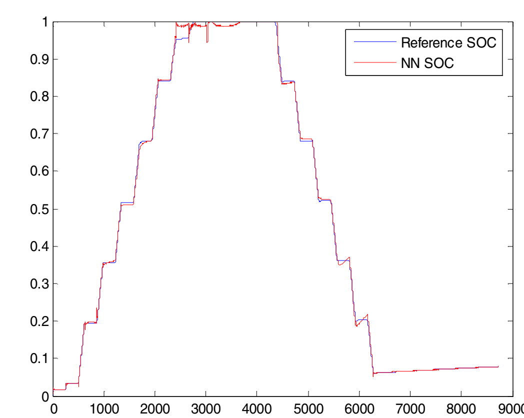


Figure 8. The performance of NN with method 4 SOC input on U1-12XP data

The test performance of NN-EKF model on MH-AAA 1000 data are in the Table 6, since the temperature is considered in this data set, we can get more accurate result than U1-12XP data. The best performance 0.36% is still obtained by NN-EKF with Method 4.

TABLE 6 THE PERFORMANCE OF NEURAL NETWORK COMBINING WITH EKF METHOD (NN-EKF) ON MH-AAA 1000 DATA

Method	Description	NN-EKF SOC (%) Root Mean Square Error	EKF SOC (%) Root Mean Square Error
1	Charge OCV curve	0.71	2.0212
2	Discharge OCV curve	0.44	2.6408
3	Mean OCV curve	0.52	3.4800
4	Split OCV curve	0.36	0.8716

The estimated SOC get from NN-EKF method for NiMH battery shown in Fig. 9

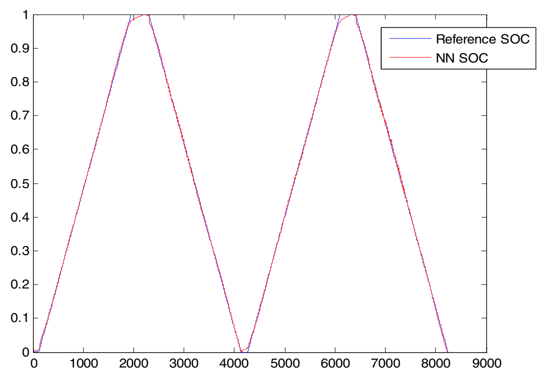


Figure 9. The performance of NN with method 4 SOC input on MH-AAA 1000 data

From all of the above experimental results we presented, we can see the performances of NN-EKF method are not only better than the neural network method without SOC from EKF, also better than those EKF methods themselves. Consistently we also find the best performance for either Li-ion data or NiMH data in NN-EKF method is used the SOC from EKF method 4 as input.

VI. CONCLUSION

In this paper, we made two contributions. First we presented an EKF based battery modeling algorithm that addresses the impact of battery hysteresis based on split OCV curves. Secondly, we proposed a SOC estimation model, NN-EKF, that integrates a neural network with the EKF for effective dynamic operation.

Both the EKF model and the NN-EKF model have been evaluated through experiments conducted on data acquired from two different batteries. The experimental tests showed that the proposed NN-EKF method gave SOC estimation with the error less than 1%, which is better than many recently published results [1-3]. In particular, the NN-EKF that uses the split OCV for charge and discharge gave the top performances in both experiments. In conclusion, the proposed EKF modeling based on split OCV curves, and the NN-EKF system for SOC estimation can accurately model the dynamic behavior of both the Lithium-ion and Ni-MH batteries, which makes it appropriate for HEV application.

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