# An Improved Extreme Learning Machine Model and State-of-Charge Estimation of Single Flow Zinc-Nickle Battery

**Xiaofeng Lin, Yang Guo, Jie Cheng, Zhenbang Guo and Xinglong Yan**

Redox flow battery was first funded by NASA. In 1974, Thaller proposed this new type of battery and applied for a patent on it. After several decades of development, the researchers have developed a variety of double-flow battery systems. However, the double-flow battery uses two kinds of electrolyte, which requires expensive ion-exchange membrane. Therefore, there are many disadvantages in those battery systems, such as cross-contamination of electrolyte high cost, large volume and low specific energy.

In 2004, Pletcher's team developed a single-flow lead-acid battery with no ion-exchange membrane [1]. This battery requires only one tank and one pump compared to the double-flow battery. Therefore, this kind of single-flow battery reduces the cost and simplifies the structure of the flow battery. It also provides a new idea for the development of flow battery. In 2007, Yang Yusheng and Cheng Jie's team developed a new single-flow zinc-nickel battery [2].

Since the single-flow zinc-nickel battery was proposed, many scholars have studied it from different angles: Beijing Research Institute of Chemical Defense studied the effects of electrolyte and electrode materials on the cell performance. And according to the internal reaction mechanism of the battery, they established a mechanism model of charge and discharge processes in battery electrode [3]. Beijing University of Chemical Technology [4] studied the relationship of electrolyte flow rate, current density and zinc deposition area capacity. After that, the effects of them on single-flow zinc-nickel battery charge and discharge performance has been studied. Dalian Institute of Chemical Physics [5, 6] studied battery performance from the temperature and shape of the electrode material. Internationally, single-flow zinc-nickel batteries have been studied by the Energy Institute of New York City University, which in 2014 successfully increase capacity of single battery to 555Ah, and assembled a 25kWh single-flow zinc-nickel battery pack.

X. Lin (✉) · Y. Guo · J. Cheng · Z. Guo · X. Yan
School of Electrical Engineering, Guangxi University, Nanning, China
e-mail: gxulinxf@163.com



Z. Deng (ed.), *Proceedings of 2017 Chinese Intelligent Automation Conference*,
Lecture Notes in Electrical Engineering 458,
https://doi.org/10.1007/978-981-10-6445-6_67

The experimental results show that, after 1000 cycles of 100% Depth of Discharge (DoD) tests, battery pack still keep energy efficiency above 80% [7]. This is a breakthrough of single-flow zinc-nickel battery application.

# 1 Model of Single Flow Znic-Nickle Baterry

Battery as large energy storage device needs a accurate model to describe its charge/discharge status and voltage characteristics. The existing battery model could be divided into electrochemical model, equivalent circuit model and neural network model. The electrochemical model establishes a positive and negative electrode model by analyzing the electrode dynamics, diffusion and mass transfer processes. This kind of model has high accuracy, but it is too complex and difficult to be applied in actual application. Equivalent circuit model uses voltage source, resistance and capacitance components to establish a battery model. This kind of model can simulate the change of battery terminal voltage during charge/discharge process and the analysis method of this model is clearer and can be deduced from the theoretical basis of the circuit. Therefore, this modeling method is widely used in research on external characteristic and dynamic response of battery.

Artificial Neural Network (ANN) model is based on the battery variable parameters of charge/discharge process, such as voltage, current, internal resistance, temperature etc. By self-learning and parallel processing capabilities of neural network, this kind of model can obtain non-linear mapping relation between battery data and establish battery model. At present, the widely used neural network models include BP network model, RBF network model [8] and Extreme Learning Machine (ELM) model [9].

However, because the inputs of ELM are based on the voltage of previous time, SoC and current of present moment, so when a great change occurred in current, ELM often cannot accurately track the instant step change of battery voltage. In this article, based on the advantages of ELM network and the equivalent circuit model, an improved Extreme Learning Machine model of data driven and equivalent circuit is established, and compared this proposed model with simple ELM network model, the superiority of improved ELM model is verified.

## *1.1 Extreme Learning Machine*

The algorithm process of ELM will be described below. The training set is defined as $x_i = (x_{i,1}, x_{i,2} \ldots, x_{i,N})^T \in R^N$, $t_i \in R$. Here, N is the input-output sample number of the training set. The activation function g(x) which is differentiable on arbitrary interval is determined before training. For the standard Single-hidden layer feed forward neural network with L hidden nodes, the output model of the network is

$$\sum_{i=1}^{L} \beta_i(\alpha_i x_i + b_i) = t_j \quad j = 1\ldots N \quad b_i, t_j \in R, \quad \alpha_i \in R^N \tag{1}$$

where $\alpha_i$ is input weight vector $\alpha_i = (\mathrm{a}_{i1}, a_{i2}\ldots, \mathrm{a}_{iN})^T$, $b_i$ is hidden layer bias and $i$ represents the $i$th hidden node. $\beta_i$ is the output weight connecting the $I$ th hidden node and output node; $\alpha_i x_i$ is the inner product of $\alpha_i$ and $x_i$; $t_j$ is the $j$th input-output sample; (1) can be written in the equivalent form $H \cdot \beta = T$, where

$$H = \begin{bmatrix} g(\alpha_1, b_1, \mathrm{x}_1), & \cdots, & g(\alpha_L, b_L, \mathrm{x}_1) \\ \vdots & \cdots & \vdots \\ g(\alpha_1, b_1, \mathrm{x}_N), & \cdots, & g(\alpha_L, b_L, \mathrm{x}_N) \end{bmatrix}$$

$$\beta = [\beta_1, \beta_2 \ldots \beta_L]^T, \quad T = [t_1, t_2, t_3]^T$$

$H$ is the hidden layer output matrix. The input weights of network parameters and the biases of hidden layer neurons are given randomly. Therefore $\beta$ is the only parameter which needs to be calculated in network. This means it is necessary to find $\hat{\beta}$ which make

$$\left\| H\hat{\beta} - T \right\| = \min_{\beta} \| H\beta - T \| \tag{2}$$

Huang et al. [10] has shown that the least squares solution of above equation is

$$\hat{\beta} = \mathrm{H}^{+} T \tag{3}$$

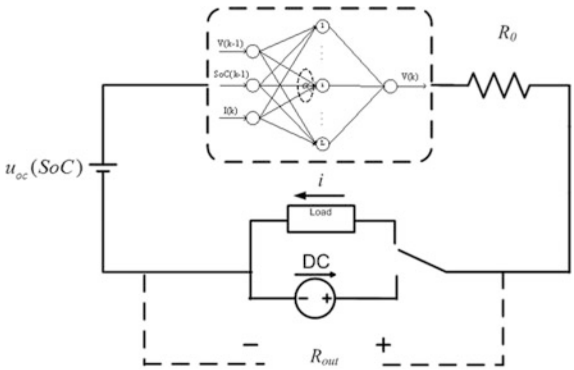
where $H^{+}$ is the Moore-Penrose generalized inverse of H.

It can be seen that the ELM network does not need to iteratively adjust parameters of network, only need to solve the network output weight matrix once by the number of hidden neurons and the neuron activation function. It means great improvement in network learning speed and obtaining the global optimal solution of network parameters.

## 2 The Proposed Model of Single Flow Zinc-Nickel Battery

As shown in Fig. 1, the single-flow zinc-nickel battery model in this paper is an improved ELM model which consists of voltage source, resistance and data-driven ELM model.

**Fig. 1** Improved ELM model of single flow zinc-nickel battery




This model can simulate the variation of terminal voltage during charge and discharge process. In this model, the voltage source $U_{OC}(\mathrm{SoC})$ describes the relationship between battery open-circuit voltage $U_{OC}$ and battery SoC. $R_0$ is ohmic resistance which describes the losses caused by electrodes, electrolytes, and contact resistance. This resistor can also explain the step change in battery terminal voltage when a large change occurred in battery current. Open-circuit voltage and ohmic resistance can be obtained by the method of Ref. [11]. ELM model is used to describe the changes in polarization voltage when SoC and battery current changed. To establish the ELM model of single flow zinc-nickel battery, first need to determine the network input and output variables. The following is commonly used battery equivalent circuit model expression:

$$V_{out}(k) = f(Soc(k)) + I(k)R_0 + U_{R_1C_1}(k) + U_{R_2C_2}(k) \tag{4}$$

$$U_{R_1C_1}(k) = U_{R_1C_1}(k-1)\mathrm{e}^{-T/R_1C_1} + I(k)R_1(1 - \mathrm{e}^{-T/R_1C_1}) \tag{5}$$

$$U_{R_1C_1}(k) = U_{R_1C_1}(k-1)\mathrm{e}^{-T/R_1C_1} + I(k)R_1(1 - \mathrm{e}^{-T/R_1C_1}) \tag{6}$$

It can be seen that there is a non-linear relationship in battery output voltage $V_{out}(k)$ at time k with battery State-of-Charge $SoC(k)$, battery current $I(k)$, battery polarization voltage ($U_{R_1C_1}(k)$, $U_{R_2C_2}(k)$) and other factors at same time. As shown in Eqs. (5) and (6), the polarization voltage of the battery at each sampling time is affected by polarization voltage ($U_{R_1C_1}(k{-}1)$, $U_{R_2C_2}(k{-}1)$) at time $(k-1)$ and battery current $I(k)$ at same time. Therefore this paper selects polarization voltage $V(k)$ of cell at time $k$ as the ELM network output variable $t(k) = V(k)$ and selects current $I(k)$ and $SoC(k-1)$ at time $k$, polarization voltage $V(k-1)$ at time $(k-1)$ as the network input vector $x(k) = [V(k-1)SoC(k-1)I(k)]^T$.

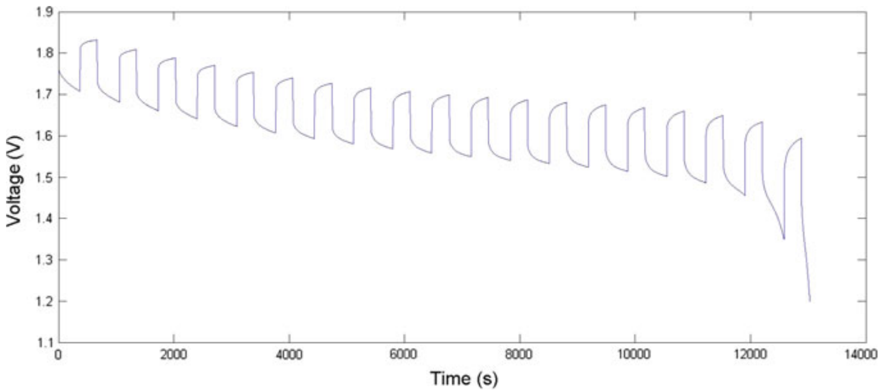



**Fig. 2** Voltage curves of pulsed discharge

## 3 Obtain Training Data

The test battery is 200 Ah single flow zinc-nickel battery. In order to make experimental data as much as possible to cover the working scope of battery and make battery model more accurate, this paper uses the intermittent discharge test on battery. The test system records battery terminal voltage, current and battery capacity during discharge process to obtain training data and test data of the network. Figure 2 is voltage curves of pulsed discharge.

## 4 Establishment and Verification of Model

Based on the experimental data obtained in the previous section, all training samples and test samples were normalized to reduce the adverse effect of data variation on network training. The activation function $g(x)$ was selected as sigmoid function:

$$g(x) = \frac{1}{e^{-x} + 1} \tag{7}$$

The number of hidden layer neurons, L was set to 100. In order to verify the superiority of proposed model, a simple ELM model of single flow zinc-nickel battery was also established and trained by same data sample. The number of hidden layer neurons in simple ELM model was also set to 100 to ensure consistency with ELM network part of proposed model. Finally, another group of discharge current was used to verify the generalization performance of the two models.

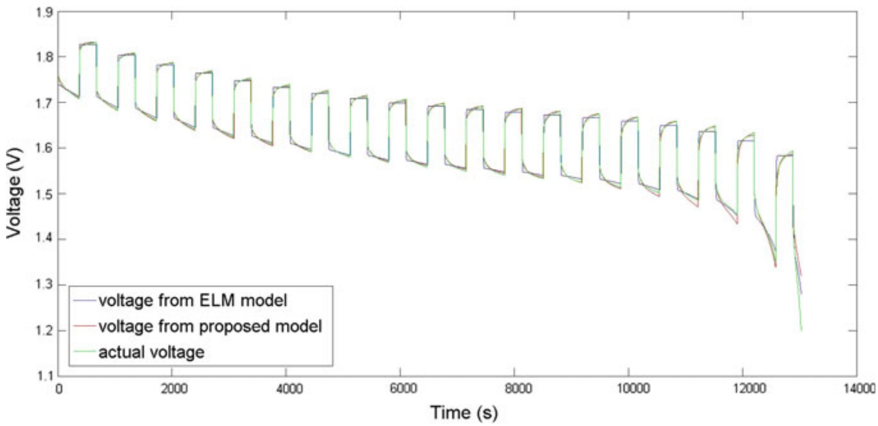



**Fig. 3** Actual voltage and output voltage of model

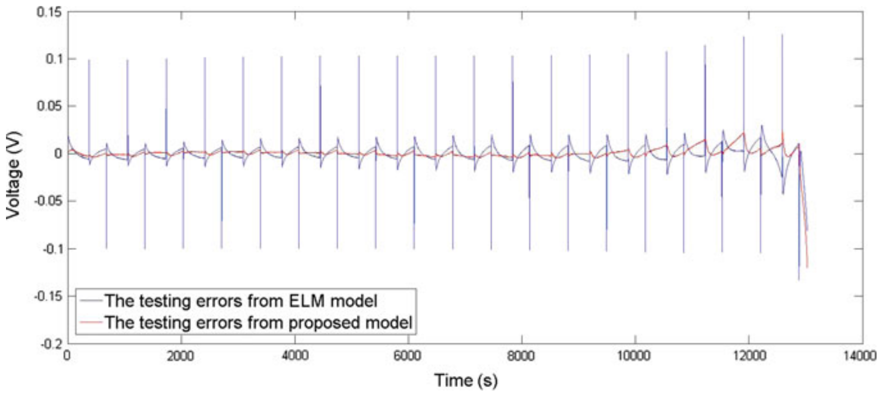



**Fig. 4** Output voltage error of two models

Figures 3 and 4 are comparisons between output voltage and actual voltage and output error curves of two models at two different discharge currents. It can be seen that proposed model is more accurate in simulating actual voltage variation of battery during standing time. And when current changes greatly, simple ELM model can not accurately track the variation of battery output voltage which would increase the error of model. But because of ohmic resistance, the proposed model can react more quickly than simple ELM model. The root mean square error (RMSE) of improved ELM model is 0.0077 V, which is less than 0.0106 V of simple ELM model. So it can be said that the proposed model is more accurate than simple ELM model.

# 5 State-of-Charge Estimation Strategy of Single Flow Zinc-Nickel Batteryssas

SoC is an important state variable in battery operation. It directly describes the remaining capacity of battery, and is also an important guarantee for battery safe operation. However, the SoC of battery can not be directly measured, and affected by many factors, so it has been a hot and difficult subject in the research of energy storage.

In this section, based on improved ELM model model established in Sect. 2, the adaptive unscented Kalman filter which is based on covariance matching is used to estimate the SoC variation of single flow zinc-nickel battery under intermittent discharge test. By comparing with AUKF based on simple ELM model, the superiority of AUKF based on proposed model is verified.

## *5.1 Battery State-of-Charge Estimation Based on Adaptive Unscented Kalman Filter*

In this paper, Adaptive Unscented Kalman Filter are not described in detail.the state space equation and output equation of battery must be established when using AUKF algorithm to estimate battery SOC. According to improved ELM model of battery established in Sect. 2, the expressions of battery model can be obtained as:

$$V(k) = \sum_{i=1}^{L} \beta_i \frac{1}{\left(\mathrm{e}^{-(\alpha_i[V(k-1)Soc(k-1)I(k)]^T + b_i}\right) + 1} \tag{8}$$

$$R(k) = \sum_{j=1}^{10} A_{(j)} SoC^{(j)}(k) + A_{(j+1)} \tag{9}$$

$$V_{OCV}(k) = \sum_{j=1}^{10} B_{(j)} SoC^{(j)}(k) + B_{(j+1)} \tag{10}$$

$$V_{out}(k) = V(k) + R(k)I(k) + V_{OCV}(k) \tag{11}$$

where $\alpha_i$ is input weight vector, $b_i$ is hidden layer bias, $\beta_i$ is output weight and $i$ represents the $i$th hidden node. $R(k)$ and $V_{OCV}(k)$ are the values of the ohmic resistance and the open circuit voltage at time $k$ fitted with 10th order equations, respectively. $I(k)$ and $V_{out}(k)$ are current excitation and terminal voltage of the battery at time K, respectively.

According to the current integration method, the calculation equation of battery SoC can be obtained as:

$$SoC = SoC(0) + \int_0^t \frac{\eta I(t)}{C_n} dt \tag{12}$$

where $\eta$ is battery charge and discharge efficiency. It is generally assumed that $\eta = 1$ in charge process and $0 < \eta < 1$ in discharge process. $SoC(0)$ is initial value of SoC. $C_n$ is battery rated capacity, for 200Ah single flow zinc-nickel battery, $C_n = 200\,\text{Ah}$. And $i(t)$ represents the real-time current of battery and it is positive in charge, negative in discharge. The discretization of (12) is:

$$SOC(k) = SOC(k-1) + \eta \frac{I(k-1)T}{C_n} \tag{13}$$

Combining battery model and current integration method expression, taking battery model output voltage $V(k-1)$ and $SOC(k-1)$ at time $k-1$ as state variables, and model output voltage $V_{out}(k)$ at time k is taken as output variable. The state equation and output equation of battery model can be obtained as:

$$\begin{bmatrix} V(k) \\ SOC(k) \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{L} \beta_i \frac{1}{\left(e^{-(\alpha_i[V(k-1)SoC(k-1)I(k)]^T + b_i)} + 1\right)} \\ SOC(k-1) + \eta \frac{I(k)T}{C_n} \end{bmatrix} + w_{1,k} \tag{14}$$

$$V_{out}(k) = V(k) + (\sum_{j=1}^{10} A_{(j)} SoC^{(j)}(k) + A_{(j+1)}) I(k) + \sum_{j=1}^{10} B_{(j)} SoC^{(j)}(k) + B_{(j+1)} v_{1,k} \tag{15}$$

where $w_{1,k}$ and $v_{1,k}$ are process noise and measurement noise, respectively.

## 6 Experimental Verification and Analysis

In order to verify the estimation ability of above algorithms, AUKF algorithm based on proposed model and AUKF based on simple ELM model are used to estimate the variation of battery SoC under pulsed discharge as described in Sect. 2. In most cases, the initial value of SoC can not be accurately obtained and this is one of the reasons why current integration method can not accurately estimate battery SoC. Therefore, a good estimation algorithm should have good anti-jamming ability for initial SoC error. In order to verify the robustness of above algorithms to initial error, the initial SoC value is set to 80%, but actual initial value is 100%. Figure 5 and Fig. 6 are estimation results and estimation errors of two algorithms. Both AUKF based on proposed model and AUKF based on simple ELM model show strong ability to correct initial error of SoC. But under same ELM network

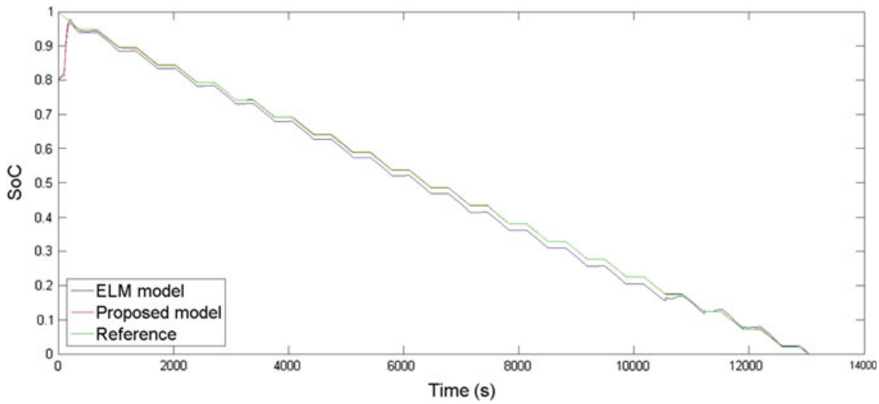



**Fig. 5** Estimated SoC of AUKF based on proposed model and AUKF based on simple ELM model

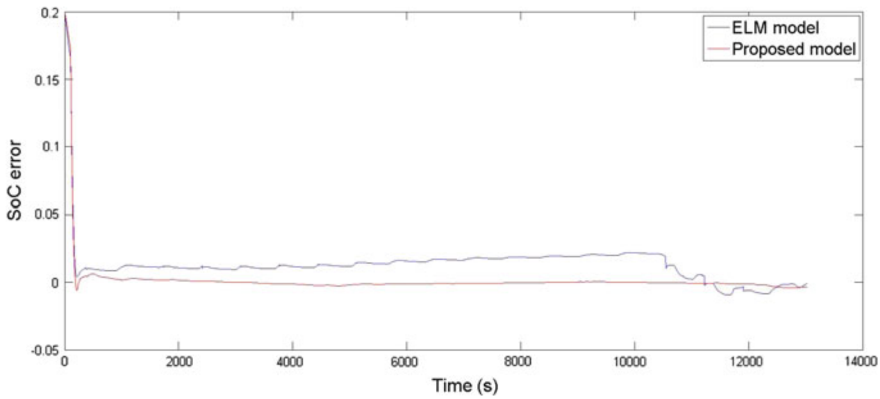



**Fig. 6** Estimated SoC of AUKF based on proposed model and AUKF based on simple ELM model

model, the RMSE of AUKF based on proposed model is 0.0178, and RMSE of AUKF based on simple ELM model is 0.0222. Therefore, it can be said, AUKF based on proposed model improves the accuracy of estimation.

## 7 Conclusion

A novel redox flow battery–single flow Zinc-Nickle battery is introduced in this paper. Based on battery simple ELM model, this paper proposes a improved ELM model model combined with equivalent circuit and ELM for the problem that simple ELM model can not track the variation of voltage rapidly when current changes greatly. It is proved that the proposed model can simulate the variation of battery terminal voltage during discharge process with higher precision. Finally, based on this improved ELM model model, AUKF algorithm is used to estimate battery SOC, which proves that the proposed algorithm can converge quickly and has higher precision compared with AUKF based on simple ELM model. The study provides a basis for the control, optimization and energy conversion of single flow Zinc-Nickle battery energy storage system, and also provides a reference for its further research and application.

**Acknowledgements** The project supported by the National Natural Science Foundation of China No. 61364007.

## References

1. Pletcher D, Wills R (2005) A novel flow battery—a lead acid battery based on an electrolyte with soluble lead (II): III. The influence of conditions on battery performance. J Power Sources 149:96–102
2. Cheng J, Zhang L, Yang YS, Wen YH, Cao GP, Wang XD (2007) Preliminary study of single flow zinc–nickel battery. Electrochem Commun 9(11):2639–2642
3. Liu X, Cheng J, Xie Z, Cao G (2011) Process in mathematical models of the nickel hydroxide electrode. Mater Rev 3:024
4. Shiye S, Junli P, Yuehua W, Jie C, Junqing P, Gaoping C (2014) Effects of electrolyte flow speed on the performance of Zn-Ni single flow batteries. Chem J Chin Univ 35(1):134–139
5. Cheng Y, Zhang H, Lai Q, Li X, Zheng Q, Xi X, Ding C (2014) Effect of temperature on the performances and in situ polarization analysis of zinc–nickel single flow batteries. J Power Sources 249:435–439
6. Cheng Y, Zhang H, Lai Q, Li X, Shi D, Zhang L (2013) A high power density single flow zinc–nickel battery with three-dimensional porous negative electrode. J Power Sources 241:196–202
7. Turney DE, Shmukler M, Galloway K, Klein M, Ito Y, Sholklapper T, Banerjee S (2014) Development and testing of an economic grid-scale flow-assisted zinc/nickel-hydroxide alkaline battery. J Power Sources 264:49–58
8. Charkhgard M, Farrokhi M (2010) State-of-charge estimation for lithium-ion batteries using neural networks and EKF. IEEE Trans Industr Electron 57(12):4178–4187
9. Du J, Liu Z, Wang Y (2014) State of charge estimation for Li-ion battery based on model from extreme learning machine. Control Engineering Practice 26:11–19
10. Huang GB, Zhu QY, Siew CK (2006) Extreme learning machine: theory and applications. Neurocomputing 70(1):489–501
11. Kim T, Qiao W (2011) A hybrid battery model capable of capturing dynamic circuit characteristics and nonlinear capacity effects. IEEE Trans Energy Convers 26(4):1172–1180