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ZEBRA battery SOC estimation using PSO-optimized hybrid neural model considering aging effect

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Abstract: The state of charge (SOC) estimation for electric vehicles (EVs) is important and helps to optimize the utilization of the battery energy storage in EVs. In this way, aging is also a key parameter impacting the performance of batteries. In this paper, a hybrid neural model is proposed for the SOC estimation of ZEBRA (Zero Emission Battery Research Activities) battery considering the aging effect through the state of health (SOH) and the discharge efficiency (DE) parameters. The number of hidden nodes in neural modules is also optimized using particle swarm optimization (PSO) algorithm. The SOC estimation error of the proposed system is 1.7% when compared with the real SOC obtained from a discharge test.

Keywords: hybrid neural networks, state of charge, estimation, PSO algorithm

Classification: Electron devices, circuits, and systems

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1 Introduction

Recently, using battery modules in either solar, electric or hybrid electric vehicles is being further quested. There are several researches each of which figuring out characteristics of different battery types, many of which unfortunately lack the aging effect [1] to [5]. On the other hand, Ah counting is not an acceptable method for the state of charge (SOC) estimation of a battery, as the initial SOC and coulombic efficiency are difficult to measure [4]. Also, offset and long term state divergence are the main problems of a traditional SOC indicator. The SOC estimation has become an important research topic in hybrid electric vehicle (HEV) industry, so the driving range cannot prevent HEVs from stranding on the road and the performance of battery management system will be optimized. Several methods have been proposed for SOC estimation that most of them use artificial neural networks (ANNs) [1], [5] to [8] or variants of Kalman filters [4, 9, 10]. In this paper, a hybrid neural model is proposed for SOC estimation of a ZEBRA (Zero Emission Battery Research Activities) battery in which the state of health (SOH) and the discharge efficiency (DE), as two parameters that consider the aging effect, are determined by two ANNs. The number of hidden layer nodes of multi-layer perceptron (MLP) modules in the proposed hybrid ANN model is optimized by particle swarm optimization (PSO) algorithm.

It is noted that determination of the optimal architecture of a neural network is crucial, because it ensures good generalization by reducing the occurrence of overfitting. Several studies have been done to develop pruning algorithms for networks [11]. On the other hand, genetic algorithm (GA) and PSO technique have attracted considerable attention among various modern heuristic optimization techniques [12]. The drawback of the GA is its high computational load. PSO has the same effectiveness (finding the true global optimal solution) as the GA but with significantly better computational efficiency (less function evaluations) [13, 14]. In other words, PSO arrives at its final parameter values in fewer generations than the GA.

In this work, the standard 21.2 kWh ZEBRA battery (type Z5) with a peak power of 32 kW and weight of 180 kg is used in the simulations. The ZEBRA battery module has been utilized successfully in prototype HEVs, because it exhibits high energy density; i.e. 3-4 times higher than lead-acid and 2-3 times higher than Nickel Metal Hybrid (Ni-MH) batteries. The pulse power capability is also adequate for typical HEVs acceleration profiles, at around 50% further than the rated energy. The ZEBRA cells also offer significantly increased cycle life $\approx$ 3500 nameplate cycles that is 7-8 times higher than lead-acid batteries. It is noted that the proposed learning-based method uses the ZEBRA battery data without loss of generality. In other words, this method can work when using the data of other kinds of battery.

The paper is organized as follows. In Section 2, the battery aging effect is discussed. The PSO algorithm is reviewed in Section 3. The proposed model is introduced in Section 4. Simulation results are reported in Section 5 and conclusions are provided in Section 6.

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2 Battery aging effect

Aging is also referred as battery memory effect or battery degradation, and is measured in terms of SOH [15]:

$$SOH = \frac{C_{INS}}{C_{REF}} \tag{1}$$

in which C_{INS} is the instantaneous capacity and C_{REF} is the battery capacity when it is recently installed. The inputs of battery SOC estimation system are variables such as battery terminal voltage, discharge current and battery temperature. Because of nonlinear dependency of SOC on the mentioned variables and respecting to Peukert equation [16], a successful SOC estimation system can utilize ANN or other intelligent algorithms. The DE is another key parameter for considering actual battery conditions. In this way, the open circuit voltage (OCV) across battery terminals can be used to determine SOH.

3 PSO algorithm

In PSO, there is a group of particles that look for the best solution within the search area. If a particle finds a better value for the objective function, the particle will communicate this result to the rest of the particles. In this algorithm, each particle has a velocity and a position as follow [17]:

$$v_i(k+1) = v_i(k) + \gamma_{1i}(P_i - x_i(k)) + \gamma_{2i}(G - x_i(k)) \tag{2}$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{3}$$

where i is the particle index, k is the discrete time index, v_i is the velocity of ith particle, x_i is position of ith particle, P_i is the best position found by ith particle (personal best), G is the best position found by swarm (global best) and γ_{1i} and γ_{2i} are random numbers in the interval [0,1] applied to ith particle. In our simulations, the following equation is used for velocity [18]:

$$v_i(k+1) = \varphi(k)v_i(k) + \alpha_1[\gamma_{1i}(P_i - x_i(k))] + \alpha_2[\gamma_{2i}(G - x_i(k))] \tag{4}$$

in which φ is inertia function and α_1 and α_2 are the acceleration constants.

4 Proposed model

The SOH is measurable as the battery has been switched off sufficiently, and it depends nonlinearly on the OCV and the battery residual capacity (BRC). In this paper, the SOH is determined by a MLP, and the DE is determined by another MLP and then the SOC is estimated through coloumetric algorithm (CA) (Fig. 1). So, SOH is the intermediate parameter in this scheme and we have an opportunity to monitor it.

The inputs to the CA module are DE, instantaneous current (i) and clock information (clk) to calculate BRC and SOC due to the following equations:

$$BRC(N) = BRC(N-1) - \frac{i \times clk}{3600 \times DE} \tag{5}$$

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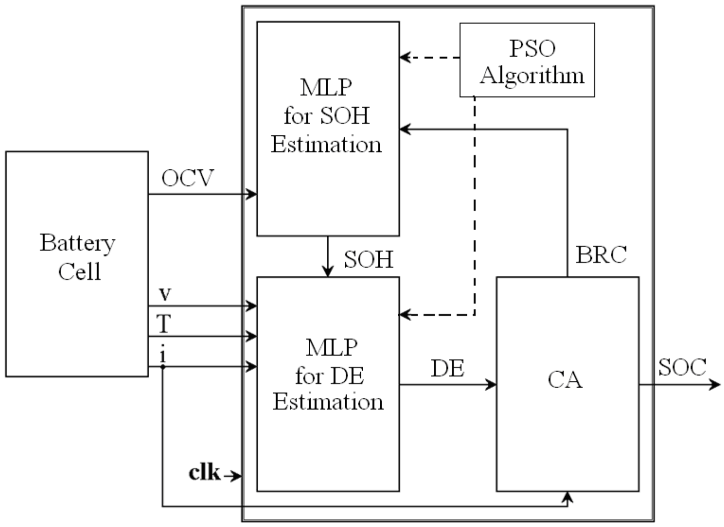

Fig. 1. Structure of proposed PSO-optimized hybrid neural model for SOC estimation

$$SOC(N) = \frac{BRC(N)}{BNC} \times 100 \tag{6}$$

where *clk* is the system clock period in seconds, BNC stands for the battery nominal capacity, N and N-1 refer to current and previous values, respectively.

In Fig. 1, T, v and i are instantaneously detected temperature, voltage and current from the battery cell, respectively. On the other hand, OCV is measureable at least two hours after battery has been switched off. The role of PSO algorithm in the proposed scheme is finding the optimum number of hidden-layer nodes of two MLPs. It is obvious that an optimum-structure neural-based estimator results in more generalization ability [19], and less estimation error as compared to a non-optimized one.

5 Simulation results

The training data for the proposed model is acquired by sampling the Z5C ZEBRA battery charge and discharge characteristics [20]. The training, validation and test datasets consist of 1800, 600 and 600 samples, respectively. The number of hidden-layer nodes of MLPs that estimate SOH and DE parameters is optimized using PSO algorithm. By setting the PSO parameters as below, the number of hidden-layer nodes of two mentioned MLPs is obtained as 8 and 37, respectively. So, the topology of two MLPs is set to [2 8 1] and [4 37 1] in our simulations, respectively:
Population size=20, Maximum particle velocity=4, Initial inertia weight=0.9, Final inertia weight=0.2 and α_1=α_2=1

The 'sigmoid' and 'linear' functions have been selected as the transfer functions of hidden layer and output layer, respectively. The resilient back-propagation algorithm (RPROP) is used for training the MLPs [21], when the minimum performance gradient and learning rate are set to 1E-6 and 0.01, respectively. The number of epochs to reach MSE=1e-6 is 223 in training MLP which estimates DE.

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The mean estimation error (MEE) is defined as follows:

$$MEE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{SOC_{estimated}(i) - SOC_{actual}(i)}{SOC_{actual}(i)}\right| \times 100\% \qquad (7)$$

in which N=600 is the number of test samples or observation points that are included to calculate error rate. The MEE of the proposed system is compared to a non-hybrid PSO-optimized MLP model with [4 25 6 1] topology when the actual SOC obtained from a discharge test of ZEBRA battery and also recent researches using Ni-MH battery (Table I).

Table I. Performance comparison of some recent models in SOC estimation

Research group	Battery type	Estimation algorithm	MEE (%)
Cheng et al. [8]	Ni-MH	Immune evolutionary	5.0
Wang et al. [4]	Ni-MH	Adaptive Kalman filtering	2.4
Xu et al. [10]	Ni-MH	Extended Kalman filtering	0.6
Hybrid neural model (proposed in this study)	ZEBRA	PSO-optimized hybrid MLP-based	1.7
Non-hybrid neural model (simulated in this study)	ZEBRA	PSO-optimized non-hybrid MLP-based	3.1

The battery efficiency (η), which is the ratio of terminal voltage to OCV, is also determined for two conditions: SOH=100% and SOH=60% (Fig. 2). As can be seen, the value of SOH has a significant impact on the efficiency of battery, especially for large values of current.

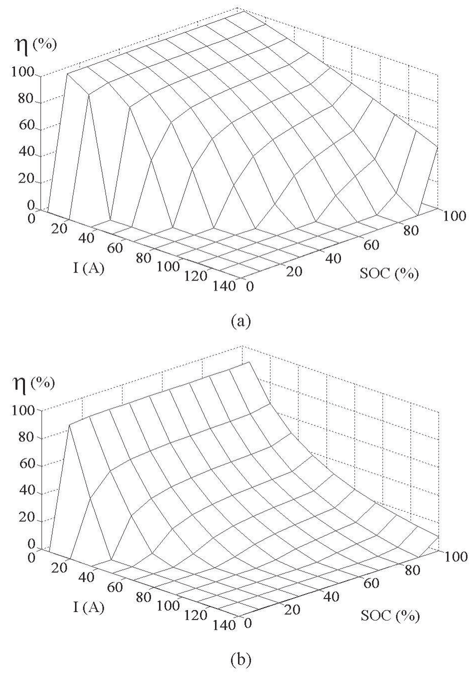

Fig. 2. Dependence of efficiency on current and SOC: (a) SOH = 100% (b) SOH = 60%

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6 Conclusions

The ability to determine SOC for EVs has become very important. The proper estimation of SOC results in optimization of battery energy storage utilization in modern EVs. On the other hand, aging is a lost but key component in the analysis of most battery management systems that estimate SOC. The relation between SOC estimation error and SOH, DE and other parameters is complex. So, the proposed scheme in this paper is employed to determine this complex and nonlinear behavior using hybrid swarm intelligence (SI)-neural based learning machine. In this way, a PSO-optimized hybrid neural model has been proposed to improve SOC estimation of ZEBRA battery considering the aging effect through SOH and DE parameters. Experimental results have shown that the proposed model is superior to the more traditional techniques with accuracy in estimating the SOC within 1.7%.

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