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BIG DATA DRIVEN LITHIUM-ION BATTERY MODELING METHOD: A DEEP TRANSFER LEARNING APPROACH

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ABSTRACT

Battery is the bottleneck technology of electric vehicles (EVs), which has complex and hardly observable inside chemical reactions. To reduce the training data volume requirement in artificial intelligent algorithm based battery model, this paper presents a deep transfer learning algorithm based battery modeling method. The Deep Belief Network - Extreme Learning Machine (DBN-ELM) algorithm is used for battery modeling issue in this paper to excavate the hidden features in battery data set and improve the accuracy and stability. The results show that the proposed transfer learning algorithm based battery modeling method is able to achieve a highly accurate simulation for battery dynamic characteristics under an insufficient data set, and the mean absolute percentage error of the established model is within 3%.

Keywords: electric vehicle, lithium-ion battery, modeling, deep learning, transfer learning.

1. INTRODUCTION

The battery and its management system are the most important components of EVs[1]. Reasonable data collection and analysis are the foundation for state estimation and fault diagnosis of the battery, and accurate battery state estimation is the premise of durability and safety management[2, 3].

The neural network algorithm has a strong nonlinear mapping ability, which can automatically learn useful knowledge from the data without an accurate mathematical model. In previous work, neural network algorithms have been widely used in battery modeling. A black box model for the battery based on Back Propagation (BP) neural network algorithm is established by Kang L W et al. [4], who designed a model that can accurately represent the highly nonlinear mapping between the input and output of the battery. To improve the accuracy and stability of the battery model, Haq I N et al. [5] used the Support Vector Regression algorithm and achieved effective results in the experimental stage. However, most of the algorithms used to model the battery can be regarded as shallow structure networks[6, 7], which have limited approximation ability to complex functions in the cases of finite samples and computational units. Therefore, the performance of ordinary neural network algorithm is always unsatisfactory.

In contrast to neural network algorithm, deep learning algorithm could effectively simulate the highly nonlinear mapping between the input and output. At present, deep learning algorithms have been widely used in electric load forecasting [8, 9], traffic speed prediction [10], energy management system [11], etc. Datong Liu et al. [12] proposed a battery modeling method based on deep belief network, the experiment results show that the biggest average error of estimated State of Charge (SoC) is less than 2.2%. However, a serious problem existing in DeepLearning algorithm based battery modeling method is that a tremendous amount of data is needed to improve the model accuracy and adaptability. For a new type of EV that has just been put into use, it is extremely difficult to get sufficient data [13]. Lacking training data, Deep learning algorithm can hardly get satisfactory effect and may even appear to be diverging.

Transfer learning is a kind of deep learning algorithm that is specially designed for reducing the requirement of the training data volume of in the deep learning model [14]. Deep transfer learning algorithm has been widely used in many fields, such as intelligent translator [15], visual tracking [16] and image classification [17].

According to aforementioned discussions, we make the first attempt to apply the deep transfer learning algorithm to battery modeling issues. The idea is to fully excavate the hidden features in battery data and reduce the training data volume requirement in deep learning algorithm based battery model.

2. METHODOLOGY

2.1 Lithium-ion battery modeling

The chemical reaction in Lithium-ion battery is extremely complex and it is difficult to be monitored directly [18], so this paper established a battery model which simulates the internal state with neural network. The modeling process is shown in Fig. 1.

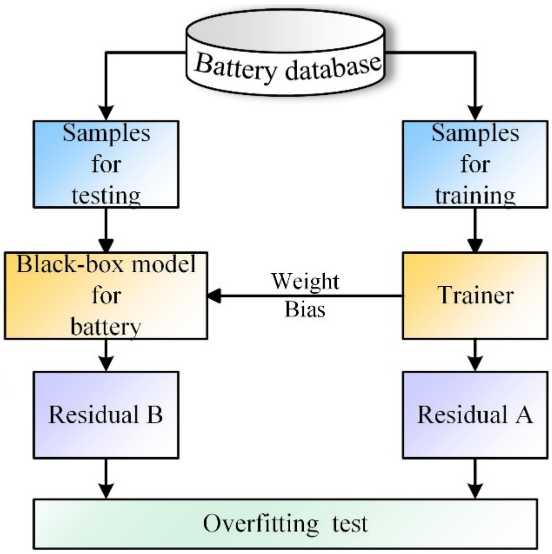

Fig. 1. The flow chart of battery modeling process

The current, temperature and SoC are used as inputs, and the terminal voltage is used as the output to model the battery in our work, the purpose of the model is to approximate the function:

$$U = f\left(SoC, I, T\right) \tag{1}$$

The basic framework of transfer learning is similar with deep learning, or more precisely, deep feature learning. Therefore, in the following section, we will detail the data feature extraction algorithm used in our work firstly, and then describe the framework of the proposed transfer learning algorithm battery modeling method.

2.2 Depth feature representation

Deep Belief Network is a semi-supervised learning model that continuously extracts the abstract features of the data layer-by-layer from the bottom-up [19]. During the data reconstruction process, the effective information in the data is retained. The re-expressed data is easier to classify or predict [20].

The Restricted Boltzmann Machine (RBM) [21] is the basic unit of the DBN. It is essentially an energy-based generation model, which can be regarded as an undirected graph model[22]. The nodes in different layers are fully connected, and there is no connection between nodes in the same layer. The structure of RBM is shown in Fig. 2.

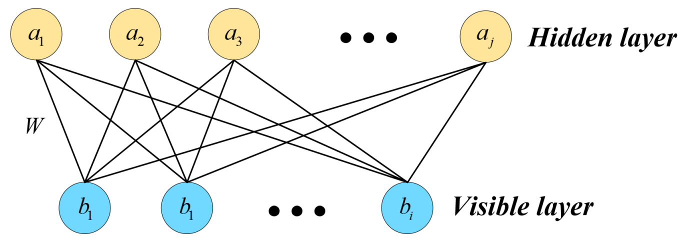

Fig. 2. The structure of Restricted Boltzmann Machine

The RBM training process is essentially the solution of the visible layer offset b, the hidden layer offset a, and the connection weight W. When the RBM state is v, h, the energy function of which can be depicted as follows:

$$E(v,h,\theta) = -b^T v - a^T h - h^T W v \tag{2}$$

According to (2), the joint probability distribution of the RBM under the state parameter θ is:

$$P(v,h\,|\,\theta) = \frac{1}{Z(\theta)} e^{-E(v,h,\theta)} = \frac{1}{Z(\theta)} e^{b^T v + a^T h + h^T W v} \tag{3}$$

Where $Z(\theta) = \sum_{h,v} e^{-E(v,h,\theta)}$ is the normalization factor.

The RBM training process is to find a set of parameters which make the joint probability distribution of the RBM largest. The traditional training method is the Markov chain Monte Carlo (MCMC) method[23]. However, in practice, this method cannot guarantee convergence. Therefore, the Contrastive Divergence (CD-k) method is used to train the RBM in this paper to ensure convergence and improve speed and accuracy.

The CD-k algorithm is essentially an improved algorithm that uses the training sample as the starting point for the MCMC state. Generally, a 1-step Gibbs sampling can obtain a sufficiently good result. The corresponding algorithm is as follows:

1) Randomly initialize model parameters $\theta = (W, a, b)$.

2) Use the unsupervised training data as visible layer vector v of the model.

3) Calculate the activation probability of the hidden layer and the visible layer according to (4) and (5):

$$h^k = p(h_j = 1 | v) = \sigma(a_j + \sum_i v_i W_{ij}) \quad (4)$$

$$v^{k+1} = p(v_i = 1 | h) = \sigma(b_i + \sum_j h_j W_{ij}) \quad (5)$$

When k=1, it should be sampled 3 times cyclically, according to the corresponding input v^0, that is, h^0、v^1、h^1, calculated respectively.

4) Update the weights and offsets according to the sampling result:

$$\Delta W = \varepsilon\left(v^{(0)}h^{(0)} - v^{(1)}h^{(1)}\right) \quad (6)$$

$$\Delta b = \varepsilon\left(v^{(0)} - v^{(1)}\right) \quad (7)$$

$$\Delta a = \varepsilon\left(h^{(0)} - h^{(1)}\right) \quad (8)$$

5) Cycle through steps 3-4 and continuously update the weights and offsets until the desired number of iterations is reached.

2.3 Deep belief network

A DBN can be regarded as a network composed of a number of RBMs [24]. As shown in Fig. 3, a DBN is formed by stacking three RBMs in this paper.

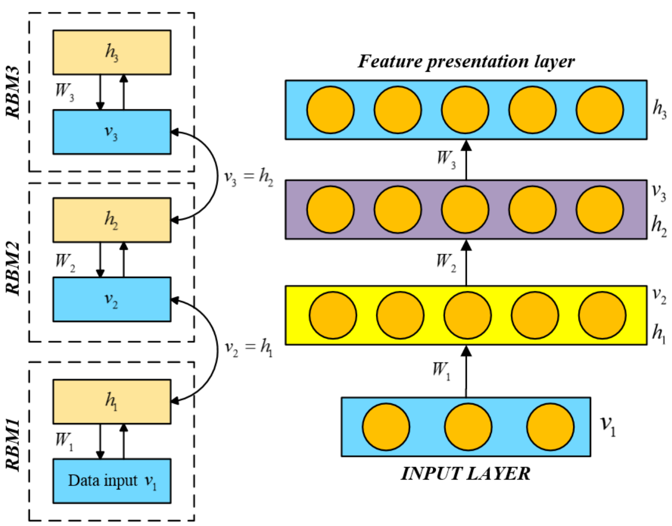

Fig. 3. The structure of Deep belief network

Each layer of the DBN is a separate RBM, which consists of a visible layer v and a hidden layer h. During training, the training data is used as the input of the visible layer h_1 of the first RBM. Then, the output of the hidden layer of the first RBM is used as the input of the visible layer v_2 of the next RBM. By analogy, the RBM is unsupervised trained from the bottom up, and the output of the hidden layer h_3 of the top-level RBM is the abstract expression of the input data.

After the training process is completed, the weight and offset of the entire network are saved. At this time, for a single restricted Boltzmann machine, the offset a of the visible layer v is no longer used, and the connection weight W becomes one-way, as shown in Fig. 4, the structure is the same as the forward neural network.

2.4 The DBN-ELM model

Extreme Learning Machine is a kind of fast learning algorithm and, actually, a neural network with a single hidden layer, but different from BP neural network, the weight and bias between the input layer and the hidden layer of the ELM are determined randomly, and the output layer has only weight but no bias. In the training process, the weight of the output layer is not solved by the gradient-based algorithm, but is transformed into a linear system for solving.

DBN-ELM is a commonly used algorithm in deep learning[25]. The DBN model is trained unsupervised from the bottom-up by unlabeled data, and it is used as a feature extractor. The output of the DBN model is used as the ELM's input; afterwards, the ELM is trained directly by labeled data and is used as the output layer of the DBN-ELM model. The structure of DBN-ELM model is shown in Fig .4.

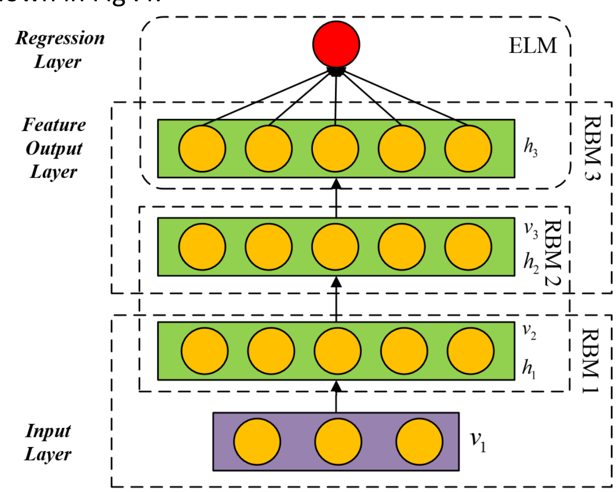

Fig. 4. The structure of the DBN-ELM model

2.5 Feature-oriented deep transfer learning method for battery modeling

To improve the accuracy of the battery model of new type of EV and reduce the requirement on training data volume, we propose a battery modeling method based on deep transfer learning algorithm in this section, as shown in Fig. 5.

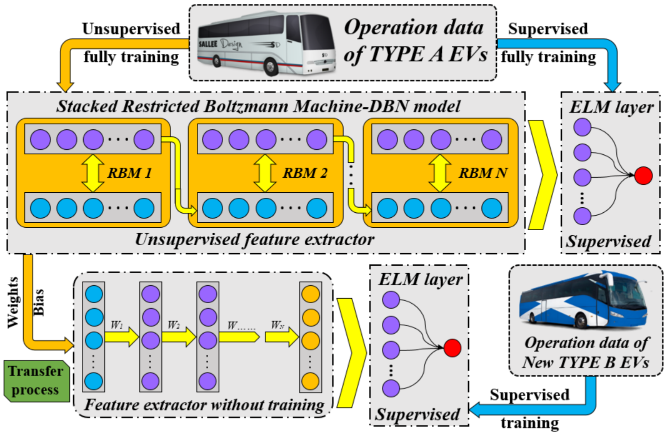

Fig. 5. The deep transfer learning algorithm based battery modeling method

In proposed transfer learning algorithm based battery modeling method, the training data are mainly derived from two sources. One is the operation data of A-type EV, which has been put into use for a long time and the training data set is sufficient. The second is from the B-type EV, which has just been put into use, the data set is insufficient. As shown in Fig. 5, the proposed modeling method consists of four steps. Firstly, the DBN algorithm based feature extractor is fully trained by using the sufficient data set from the A-type EV, so that the DBN model can fully exploit the internal characteristics of the battery data. Then, the ELM model is supervised trained to enable the DBN-ELM model the ability of modeling the battery. When the new B-type EV is put into use, the available data for model training is limited. Therefore, in the third step, the DBN feature extraction model trained in the first step is directly used in our work, which served as data feature extractor for B-type EV. Finally, only a small volume of data is required for training the ELM regression layer for B-type EV.

3. RESULT AND DISCUSSION

3.1 Experiment data set description

To obtain experimental data for verifying the battery modeling method, the battery data are continuously collected from electric buses in Beijing, China. Approximately 500000 sets of battery data under different temperature conditions and life state were collected, which include the Terminal voltage, the SoC, the temperature and the current. Fig. 6 shows the data in one discharge cycle.

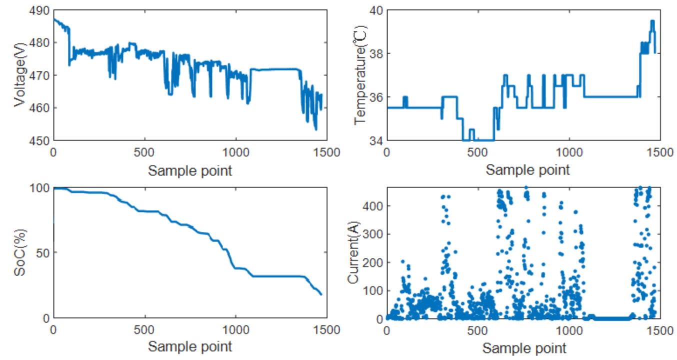

Fig. 6. The data used in this paper.

3.2 Battery modeling result

Based on the deep transfer learning based battery modeling method proposed in our work, large volume of battery data mentioned in Section 3.1 were used to train the feature extractor, and then it was transferred as the feature extractor for another type of EV battery. Approximately 500000 sets of battery data from A-type vehicle are used for DBN model training and about 50000 sets of battery data from B-type vehicle are used for final ELM model training.

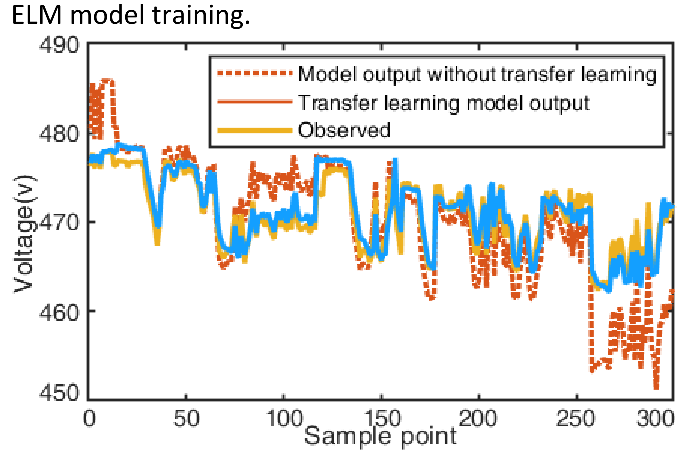

Fig. 7. The result of estimated battery terminal voltage.

The performances of proposed deep transfer learning algorithm based battery model and ordinary neural network based battery model are compared in Fig. 7. The performance of ordinary neural network based battery model is not satisfying. The reason is that the model was not fully trained with insufficient training data. The feature extractor in the proposed transfer learning algorithm based battery modeling method is fully trained, so only a small volume of data are required to train the regression layer, the accuracy of the model is effectively improved. As shown in the figure, the maximum terminal voltage estimated error can be limited within 3%.

4. CONCLUSION

This paper presents a deep transfer learning algorithm based battery modeling method. The proposed DBN algorithm based battery data feature extract method is able to fully excavate the hidden information in battery data set and improve the battery model accuracy. The ELM algorithm based regression layer used in our work has satisfying convergence speed and performance with insufficient data. The results show that the proposed battery modeling method based on DBN-ELM transfer learning algorithm is able to achieve a highly accurate simulation for battery dynamic characteristics, and the mean absolute percentage error of the established model is within 3%.

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