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A New Self-Learning TLBO Algorithm for RBF Neural Modelling of Batteries in Electric Vehicles

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***Abstract*—One of the main purposes of building a battery model is for monitoring and control during battery charging/discharging as well as for estimating key factors of batteries such as the state of charge for electric vehicles. However, the model based on the electrochemical reactions within the batteries is highly complex and difficult to compute using conventional approaches. Radial basis function (RBF) neural networks have been widely used to model complex systems for estimation and control purpose, while the optimization of both the linear and non-linear parameters in the RBF model remains a key issue. A recently proposed meta-heuristic algorithm named Teaching-Learning-Based Optimization (TLBO) is free of presetting algorithm parameters and performs well in non-linear optimization. In this paper, a novel self-learning TLBO based RBF model is proposed for modelling electric vehicle batteries using RBF neural networks. The modelling approach has been applied to two battery testing data sets and compared with some other RBF based battery models, the training and validation results confirm the efficacy of the proposed method.**

I. Introduction

The European Union has set a '20-20-20' strategy by 2020 to tackle the climate change and quick depletion of fossil fuel reserves such as coal, oil and natural gas: to reduce 20% green house gas (GHG) emission, to integrate 20% renewable energy and to improve 20% energy efficiency [1]. The passenger vehicles are one of the major contributors to GHG emissions and among the biggest users of fossil fuel reserves. The wide adoption of electric vehicles (EVs) is being encouraged to replace traditional internal combustion engine vehicles due to their advantages of low consumption of non-renewable energy resources as well as low GHG emissions [2], [3]. Many countries have set goals and favourable policies to promote the deployment of electric vehicles. Manufacturers are encouraged by these policies and the future prospects and have designed more models to compete for the market share of the conventional internal combustion engine vehicles.

The battery is one of the key elements in the development and wide adoption of EVs. The battery provides energy storage and power based on electrochemical reactions or physical mechanisms, while the behaviour of a battery is however complicated. An accurate battery model is crucial for the battery management system in order to charge/discharge properly and to estimate the state of charge (SOC) and state of health (SOH) of a battery. However, the dynamic behaviour of batteries is highly non-linear due to the complex internal electrochemistry reactions. Numerous battery modelling approaches have been introduced to estimate the complex dynamic non-linear voltage-current behaviour of batteries including white-box models such as electrochemical model, grey-box models such as equivalent electric circuit models (EECM) as well as black-box models such as neural network models [4]. Black-box models can be free of any background knowledge and easy to extend to different types of batteries.

Among all the black-box methods, the RBF neural networks have been widely used due to a simple structure and powerful approximation performance in modelling non-linear systems. One of the main challenges involved in constructing RBF network models is the optimization of parameters in the basis function. Some studies optimize the basis function parameters using gradient-based searches to manage this, but they are often trapped within a local optimum. Other methodologies based on heuristic approaches perform well in searching non-linear parameters globally and some of them have been used in battery modelling [5], [6]. However, the pre-set design parameters have a noticeable impact on the performance of these methods. A recently proposed population based heuristic method, namely Teaching-Learning-Based Optimization [7], is free of presetting the algorithm parameters and converges fast. In this paper a variant of TLBO named self-learning TLBO (SL-TLBO) is proposed to search for the non-linear parameters in the RBF model.

The rest of the paper is organized as follows. Battery models for EV applications are reviewed in Section II. A brief introduction of RBF neural networks is discussed in Section III and the basic procedure of TLBO is presented in Section IV. Then SL-TLBO based RBF modelling is demonstrated in Section V, followed by an experimental study on the modelling of a lithium-ion (Li-ion) battery in VI. Section VII concludes the paper.

II. Models for Electrical Vehicle Batteries

The battery is the major power source and energy storage device for hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs), and it is the only power source for battery electric vehicles (BEVs). The accuracy of a battery model has a significant impact on the performance of the battery management system (BMS) and consequently affects the driving experience of EV users and the life span of the battery. Numerous battery types have been used for EV

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applications including lead-acid, nickel-cadmium, nickel-metal hydride and Li-ion [8], though among which Li-ion battery is recently preferred by the leading EVs manufacturers [9] due to its high energy density and long battery life, the battery modelling approaches should be compatible with different types of batteries to tackle the rapid technique innovation.

Categorized by the modelling mechanism, battery models are divided into three types: white-box model, grey-box model and black-box model [4]. White-box battery models are normally the simulation models of real electrochemical reactions, and fundamental background knowledge such as the physical mechanism of lithium ion cell [10] are of necessity to study, leading to the complication of the modelling procedure and the failure of suitability for BMS applications. In terms of grey-box models, EECM uses circuits composed of basic electronic components to represent the behaviour of the battery such as the Thevenin-type circuit model or the impedance model [11]. The accuracy of these models is highly dependent on the circuit structure, which also needs considerable experiences. Black-box models, free of any experience of battery types and EECM structures, use neural network structures or other non-linear regression models to approximate the non-linear I-V curves, which is a convenient and robust approach to model various types of batteries [12]. The RBF network is a popular black-box model approach.

III. Radial Basis Function Networks

The RBF network is a three-layered feed forward neural network as shown in Fig.1. Consider the multi-input and single-output (MISO) RBF network, the mathematical output is formulated as

$$y(t) = \sum_{i=1}^{n} w_i \cdot \phi_i(X) \tag{1}$$

where $y(t)$ is the system output at sample time t, and w_i denotes the linear output weight for the i-th node in the hidden layer. The radial basis function ϕ_i of input vector X is chosen as Gaussian function defined below:

$$\phi_i(X) = exp(-\frac{1}{2\sigma_i^2}\|X - c_i\|^2), i = 1, 2, ..., n \tag{2}$$

where σ_i is the width and c_i denotes the center of the ith hidden node.

To model a system using an RBF network, the structure should firstly be determined, including the selection of input vector X and the number of hidden layer nodes n. In terms of choosing the RBF parameters, key parameters are divided into two sets, i.e. a non-linear parameter set θ_N including σ_i and c_i and a linear parameter set θ_L including w_i. To efficiently optimize the parameters, the development of a powerful approach still remains a key issue.

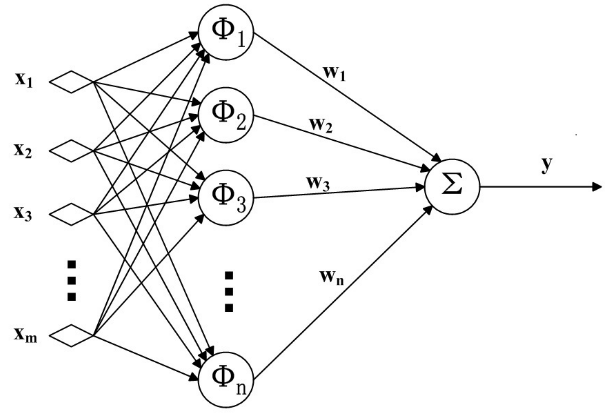

Fig. 1. RBF network structure

IV. Self Learning Teaching-Learning-Based Optimization

The TLBO is a new nature-inspired population based optimization algorithm first proposed in 2011 [7]. The philosophy of TLBO mimics a class teaching scenario where a teacher (i.e. the best student) who outperforms others in terms of grades shares his/her knowledge with the other students, and the students also learn from initiative interaction among themselves. Similar with other population based algorithms, the global solution is derived from a series of evolutions with a population of solutions. More specifically in TLBO, the population is considered as a group of students, the grade mark is analogous to the 'fitness', and the best solution obtained in one evolution is considered as the teacher.

The conventional TLBO method is divided into two parts: the teacher phase and the learner phase. In the teacher phase the learners learn from the teacher to improve the grades and in the leaner phase learners learn from the interactions between themselves. To further improve the searching speed and searching accuracy and inspired by [13], a novel step is added to follow the learner phase named self-learning phase. In this phase, each of the learners searches for better solutions around their own position, which may effectively improve the searching accuracy by the original TLBO. The modified approach is consequently named a self-learning TLBO (SL-TLBO) and the optimization procedure is given as follows.

A. Teacher Phase

In the optimization process, the best performed solution is taken as the teacher and in charge of sharing the knowledge and improving the grades of the whole class. The teaching procedure can be formulated as follows. First, the difference between the teacher and the existing mean value of all students in each dimension is denoted as DM_i

$$DM_i = rand_1 \times (T_i - T_F M_i) \tag{3}$$

where M_i is the mean value of each dimension of the solutions and T_i denotes the selected teacher at the i-th iteration. T_F is the teaching factor that determines the mean to be changed and can be either 1 or 2 denotes as:

$$T_F = round(1 + rand_2(0, 1)) \tag{4}$$

Knowledge of learners are improved by adding the DM_i as:

$$St_i^{new} = St_i^{old} + DM_i \tag{5}$$

where St_i^{new} and St_i^{old} denotes the i-th solution particles imitating learners before and after gaining knowledges. the better knowledge from new learners is accepted to replace the worse old learner.

B. Learner Phase

Besides gaining knowledge from the teacher, the learners also improve their grades through interaction between each others. They work in pairs to compare the results and share knowledge, and the process of the learner phase is denoted as:

$$St_i^{new} = \begin{cases} St_i^{old} + rand_3(St_i - St_j) & if \quad f(St_i) < f(St_j) \\ St_i^{old} + rand_3(St_j - St_i) & if \quad f(St_j) < f(St_i) \end{cases} \tag{6}$$

where the i-th learner St_i and j-th learner St_j are randomly selected from the population. The fitness values of the two learners are compared and St_i benefits from the deviation of the two learners.

C. Self-learning Phase

In the original TLBO, a new teacher is selected and shares knowledge after the learner phase, however better solutions near the learners might be missed out due to the lack of a further refinement. A self learning phase is added in order to complement the learner phase to motivate the learners to gain knowledge by themselves. The methods is formulated as follows:

$$St_i^{new} = St_i^{old} \cdot (1 + (rand - 0.5) \cdot w) \tag{7}$$

where $rand$ is a random number between (0, 1), while w is a self-learning weight that determines the learning range from learners-based knowledge. Similar with the inertia weight particle swarm optimisation (PSO) [14], w changes following the generation procedure and is formulated as:

$$w = w_{max} - \frac{G}{G_{max}} \cdot (w_{max} - w_{min}) \tag{8}$$

where G is the index of the current generation and G_{max} denotes the maximum number of generations. The self-learning weight decreases with the searching process goes on in order to shrink the solution range and to elaborately search for the painstakingly better solution. w_{max} and w_{min} are the maximum and minimum values of the self-learning weight which are selected based on the feasible solution space and the objective function. Typically, the larger the weight the wider the self searching range extends.

V. SL-TLBO BASED RBF NEURAL MODELLING

In the RBF network modelling, the root mean squared error (RMSE) based cost function is formulated as the criterion to be minimized, and it is denoted as follows:

$$min\ f = \sqrt{\frac{1}{N_m} \cdot \sum_{i=1}^{N_m} (\hat{y} - y_m)^2} \tag{9}$$

where $\hat{y}$ is the prediction value and y_m is the measured data set. Note that the formulation and all the parameters should be pre-set or determined before achieving the calculation result of $\hat{y}$ as

$$\hat{y}(t) = \sum_{i=1}^{n_h} w_i \cdot exp(-\frac{1}{2\sigma_i^2}\|X - c_i\|^2), i = 1, 2, ..., n_h. \tag{10}$$

Hence, it is necessary to formulate the RBF network first. There are three crucial steps to build a RBF network including determining the network structure, optimizing non-linear parameters as well as calculating linear parameters.

A. Determination of Network Structure

In neural network construction, the inputs and the number of hidden layer nodes need to be determined first. Considering a MISO RBF network to model a battery, the key elements of the structure include the input variables X and the number of hidden nodes n in (2). A number of approaches have been proposed to select the input vectors and the hidden layer nodes number [15], [16], [17], [18]. However, in this paper, the trial and error method is adopted to empirically select both the input vectors and the number of hidden layer nodes. The application of the above systematic methods to determine the network structure will be the future work.

B. Non-linear Parameter Optimization Using SL-TLBO

Based on the network configuration, the non-linear parameters θ_N including σ_i and c_i in (2) are optimized using the proposed SL-TLBO approach. The cost function (9) is considered as the fitness function for comparing and refining the solutions in the population during the optimization process.

C. Calculation of Linear Parameters Using Least Squares Method

Besides non-linear parameters in θ_N, the linear parameters θ_L in (1) denoting the output weights also need to be determined. The least square method is efficient to calculate θ_L as follows:

$$\theta_L = (\phi^T \phi)^{-1} \phi^T y \tag{11}$$

The detailed optimization procedure is described as

1) Initialization:
   a) select the input vector X and the number of hidden layer n_h;
   b) pre-set the generation G_m, population size N_p, upper and lower bounds of the solutions St_{up} and St_{low}.
   c) randomly generate a population of St in which the dimension of each solution is $2n_h$ as each θ_N has two unknowns σ_i and c_i.
2) Teacher Phase:
   a) compare fitness values f of all the solutions in St to select a teacher T_i;
   b) calculate the mean M_i of the population column wise (for each dimension);

c) the teacher will try to shift the mean to from M_i towards T_i. The difference between M_i and T_i is DM_i calculated in (3);
d) the obtained difference DM_i is added to the current solution to increase knowledge of learners as in (5);
e) accept better solutions in learners after teacher's influence.

3) learner Phase:
a) learners share knowledge and gain improvement through interactions aforementioned as in (6);
b) select better solutions after interaction of learners.

4) self-learning Phase:
a) learners are self motivated to gain knowledge by themselves as in (7)
b) select better solutions after learners' self-learning process.
c) back to teacher phase until arriving at the final generation or a criterion is met.

VI. Experimental Study

In this paper, a 5Ah lithium iron phosphate (LiFePO4) battery also called an LFP (lithium ferro-phosphate) battery with a maximum allowed voltage 3.65V and cut-off voltage 2.5V is tested in an Arbin BT2000 battery tester under the room temperature (25^oC). Two standard test procedures are implemented respectively. One is the Hybrid Pulse Power Characteristic (HPPC) method which is composed of a conditioning/capacity cycle, a discharge cycle as well as a charge cycle and the whole duration of the test lasts for more than 16 hours. The other procedure is the Federal Urban Driving Schedule (FUDS) lasting for more than 18 hours to simulate cycles of urban driving. A section of FUDS with SOC from (100%-90%) is selected as the training date set and the section with same of SOC in HPPC is used to validate the model. $[V(t-1), V(t-2), I(t), I(t-1), I(t-2)]$ representing voltage and current data at time t, $t-1$ and $t-2$ are the selected input X and $V(t)$ is the output, while the hidden node number is set as 7, both are based on trial and error. The total number of generations for SL-TLBO is set as 40 and the population size is set to 20, and the self-learning weight w in (7) is set as 1. Besides the SL-TLBO approach, the random selection method which generates the non-linear parameters randomly, the PSO as well as the basic TLBO approach are implemented respectively within roughly the same computational time to compare the results.

The simulation results are shown in Fig 2-5. In Fig 2, the model with randomly selected non-linear parameters sees extremely big errors. The other three optimized RBF models aided by the heuristic approaches to approximate the training data well. The maximum spike in the overall profile is 0.06 V as in Fig 3.

As the generation proceeds, the cost function decreases. All the three methods reduce the modelling error within less than ten generations and after thirty generations, the TLBO and the SL-TLBO begin to outperform the PSO. Overall SL-TLBO shows better searching capability and gives the best value.

Model validation is implemented and illustrated in Fig 4. The selected data section from the HPPC test is used as the validation data set. Fig 4 apparently shows that the three optimized RBF models approximate the battery I-V curve well, avoiding the failure approximation of the random RBF model. Validation errors of the four models are proposed in Fig 5. There are several spikes as big as 40 mV in the PSO-RBF and the TLBO-RBF models, while SL-TLBO-RBF model significantly reduces the spike to less than 7 mV. Table I compares the average deviations of validation errors for the these models. Similarly, the model with randomly selected non-linear parameter still endures extremely big errors. The PSO and the TLBO aided RBF models improve the accuracy as expected and reduce the model deviation to as low as 4.2 mV and 4.1 mV respectively. Subsequently, the SL-TLBO-aided model outperforms other alternatives and reduces the deviation to 2.1 mV. It is clear that the SL-TLBO-aided RBF model performs better on validation data and shows better generalization capability.

TABLE I
AVERAGE DEVIATION OF PREDICTION VALUE

Model Type	Random-RBF	PSO-RBF	TLBO-RBF	SL-TLBO-RBF
Average Deviation Value	12.5740	0.0042	0.0041	**0.0021**

VII. Conclusion and Future Work

In this paper, a novel SL-TLBO-aided RBF method is developed and applied to an LFP EV battery. In the SL-TLBO optimized RBF model, a modified TLBO namely self-learning TLBO is integrated to optimize the non-linear parameters in the RBF model. Compared with the model with randomly selected parameters, the PSO optimized model, as well as the basic TLBO optimized model, the SL-TLBO optimized model performs better both on the training data and the validation data, thus giving a better model generalization capacity.

Although the model shows acceptable approximation performance, some problems still remain to be solved. First, the input selection and determination of the number of hidden nodes are the two key issues in the structure configuration of the RBF model, but they are determined simply based on the empirical trial and error method in this work. The input selection can be improved by using various of input selection approaches [19], [20]. Secondly, the RMSE based cost function utilised as criterion in this work may cause the over-fitting and thus reduce the generalization capability and other criteria such as leave-one-out (LOO) [21] could be utilized to overcome this issue. Thirdly, the model structure selection and parameter optimization can be implemented continuously [22] and simultaneously [23], [24] to further improve the accuracy and generalization ability of the model. It should also be noted that the heuristically optimized RBF models which normally have expensive computation efforts, combined with the long training procedure, are more appropriate for off-line modelling. On-line battery modeling generally uses some

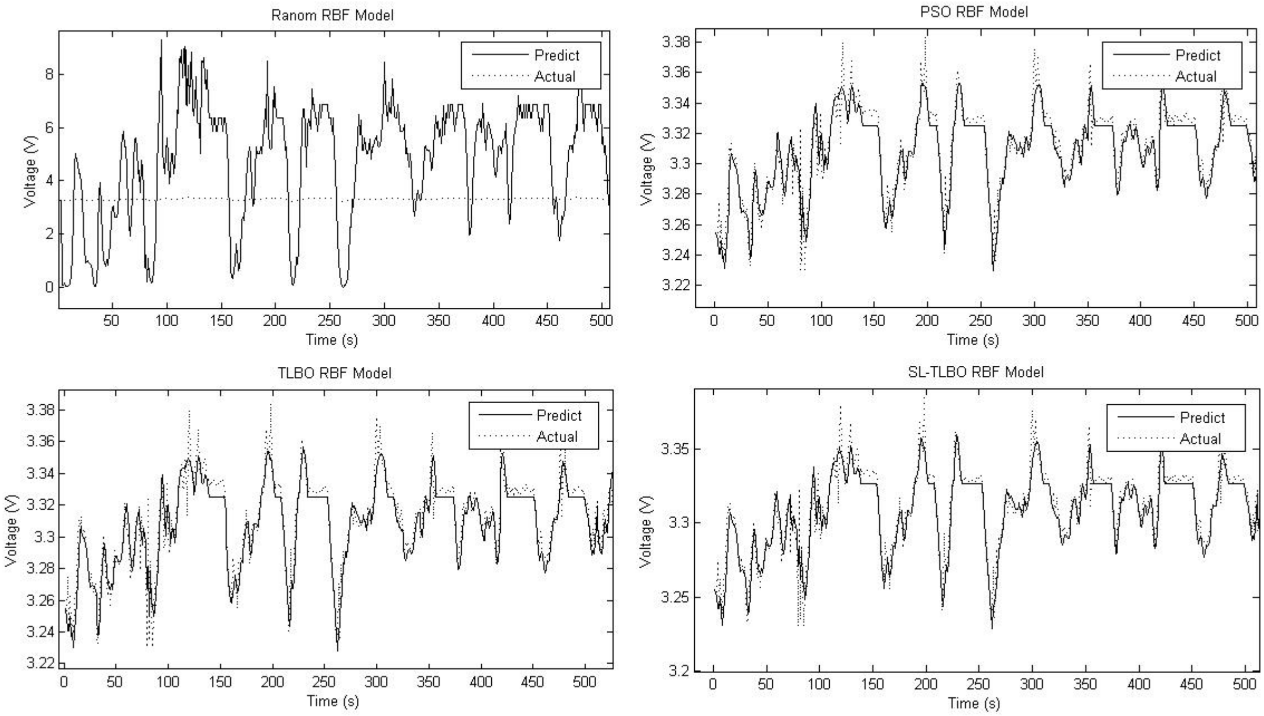

Fig. 2. Model Training Result

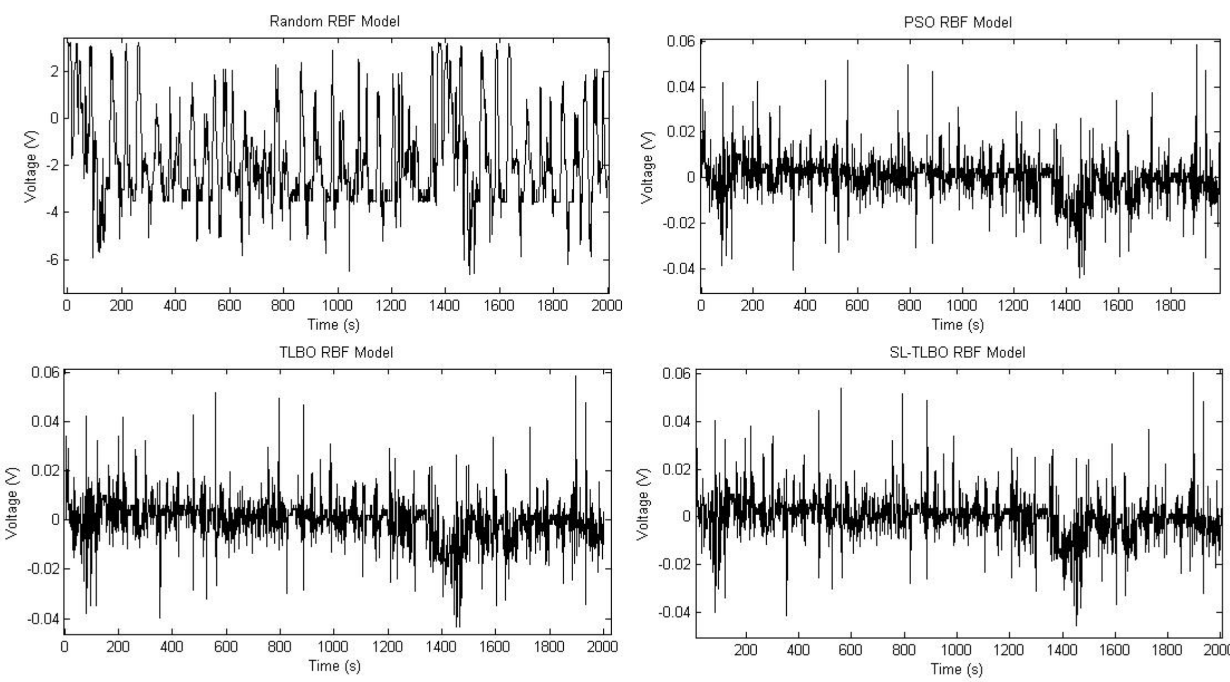

Fig. 3. Model Error

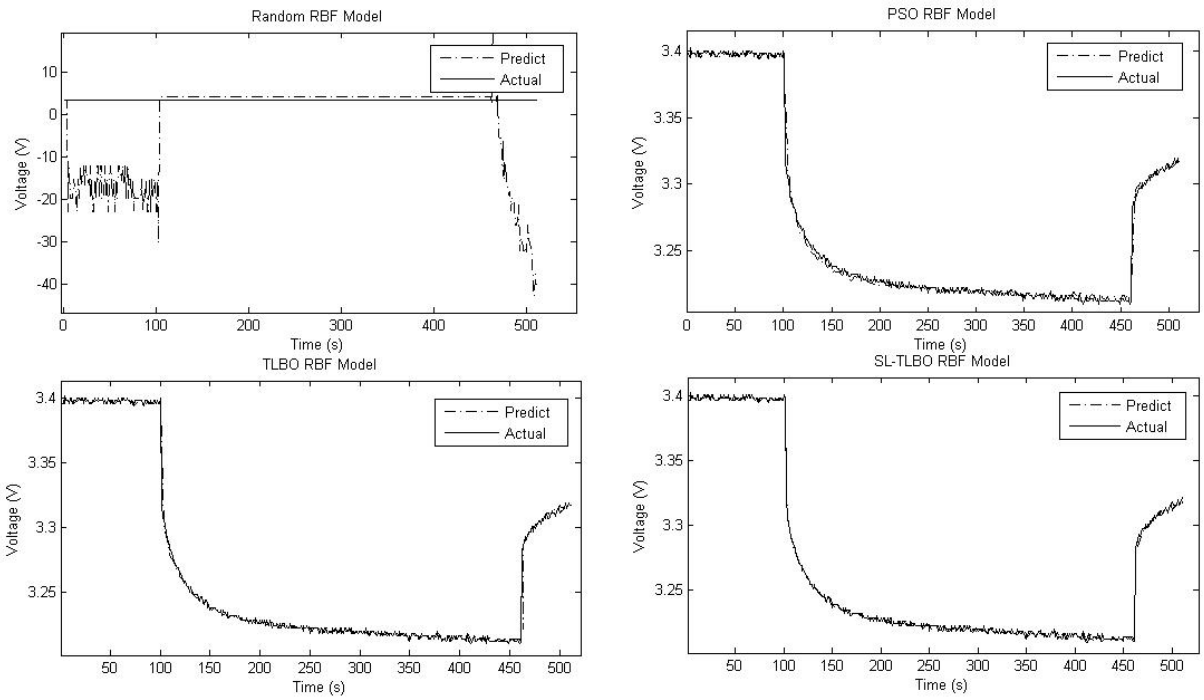

Fig. 4. Validation

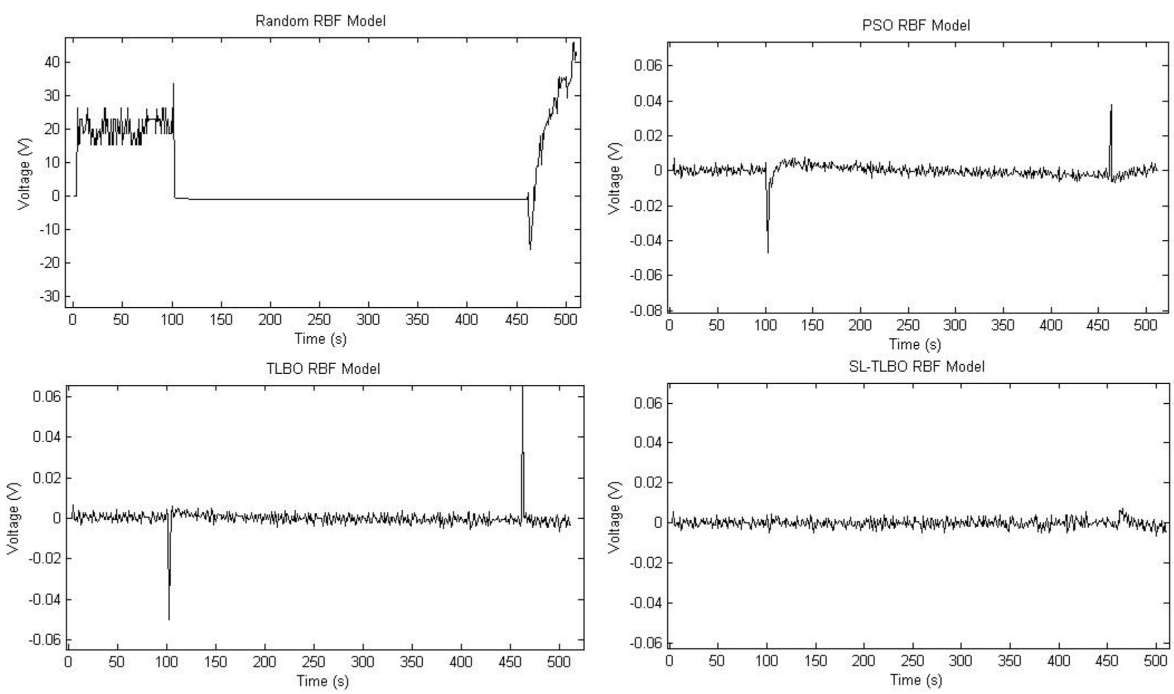

Fig. 5. Validation Error

other approaches such as the Kalman filters [25], [26]. Finally, the self-learning weight proposed in the SL-TLBO method is simply pre-set to 1 and further investigation of this parameter may potentially improve the model accuracy.

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REFERENCES

[1] *Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009-on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC*, European Union, 2009.

[2] A. Foley, B. Gallachoir, P. Leahy, and E. McKeogh, "Electric vehicles and energy storagea case study on ireland," in *Vehicle Power and Propulsion Conference, 2009. VPPC'09. IEEE*. IEEE, 2009, pp. 524–530.

[3] A. Foley, B. Tyther, P. Calnan, and B. Ó Gallachóir, "Impacts of electric vehicle charging under electricity market operations," *Applied Energy*, 2012.

[4] C. Zhang, Z. Yang, and K. Li, "Modeling of electric vehicle batteries using rbf neural networks," in *The 2nd International Conference on Computing, Management and Telecommunications*. Ieee, 2014.

[5] P. Hu, G.-Y. Cao, X.-J. Zhu, J. Li, and Y. Ren, "Modeling of a fuel cell stack by neural networks based on particle swarm optimization," in *Power and Energy Engineering Conference, 2009. APPEEC 2009. Asia-Pacific*, 2009, pp. 1–4.

[6] P. Hu, G.-Y. Cao, X.-J. Zhu, and J. Li, "Modeling of a proton exchange membrane fuel cell based on the hybrid particle swarm optimization with levenberg–marquardt neural network," *Simulation Modelling Practice and Theory*, vol. 18, no. 5, pp. 574–588, 2010.

[7] R. Rao, V. Savsani, and D. Vakharia, "Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems," *Computer-Aided Design*, vol. 43, no. 3, pp. 303–315, 2011.

[8] I. Husain, *Electric and hybrid vehicles: design fundamentals*. CRC press, 2011.

[9] J. VOELCKER. (2012) 2012 tesla model s to use panasonic lithium-ion battery cells. "http://www.greencarreports.com/news/electric-cars".

[10] T. F. Fuller, M. Doyle, and J. Newman, "Simulation and optimization of the dual lithium ion insertion cell," *Journal of the Electrochemical Society*, vol. 141, no. 1, pp. 1–10, 1994.

[11] M. Chen and G. Rincon-Mora, "Accurate electrical battery model capable of predicting runtime and i-v performance," *Energy Conversion, IEEE Transactions on*, vol. 21, no. 2, pp. 504–511, 2006.

[12] W.-Y. Chang, "Estimation of the state of charge for a lfp battery using a hybrid method that combines a rbf neural network, an ols algorithm and aga," *International Journal of Electrical Power & Energy Systems*, vol. 53, pp. 603–611, 2013.

[13] R. V. Rao and V. Patel, "An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems," *Scientia Iranica*, 2012.

[14] Y. Shi and R. Eberhart, "A modified particle swarm optimizer," in *Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational Intelligence., The 1998 IEEE International Conference on*. IEEE, 1998, pp. 69–73.

[15] K. Li, J.-X. Peng, and G. W. Irwin, "A fast nonlinear model identification method," *Automatic Control, IEEE Transactions on*, vol. 50, no. 8, pp. 1211–1216, 2005.

[16] K. Li, J.-X. Peng, and E.-W. Bai, "A two-stage algorithm for identification of nonlinear dynamic systems," *Automatica*, vol. 42, no. 7, pp. 1189–1197, 2006.

[17] S. Chen, C. Cowan, and P. Grant, "Orthogonal least squares learning algorithm for radial basis function networks," *Neural Networks, IEEE Transactions on*, vol. 2, no. 2, pp. 302–309, 1991.

[18] J. Deng, K. Li, and G. W. Irwin, "A two-stage algorithm for automatic construction of rbf neural models," in *MELECON 2010-2010 15th IEEE Mediterranean Electrotechnical Conference*. IEEE, 2010, pp. 166–171.

[19] J. Bi, K. Bennett, M. Embrechts, C. Breneman, and M. Song, "Dimensionality reduction via sparse support vector machines," *The Journal of Machine Learning Research*, vol. 3, pp. 1229–1243, 2003.

[20] K. Li and J.-X. Peng, "Neural input selectiona fast model-based approach," *Neurocomputing*, vol. 70, no. 4, pp. 762–769, 2007.

[21] S. Chen, X. Hong, B. L. Luk, and C. J. Harris, "Construction of tunable radial basis function networks using orthogonal forward selection," *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, vol. 39, no. 2, pp. 457–466, 2009.

[22] J.-X. Peng, K. Li, and G. W. Irwin, "A novel continuous forward algorithm for rbf neural modelling," *Automatic Control, IEEE Transactions on*, vol. 52, no. 1, pp. 117–122, 2007.

[23] J. González, I. Rojas, J. Ortega, H. Pomares, F. J. Fernandez, and A. F. Díaz, "Multiobjective evolutionary optimization of the size, shape, and position parameters of radial basis function networks for function approximation," *Neural Networks, IEEE Transactions on*, vol. 14, no. 6, pp. 1478–1495, 2003.

[24] A. Alexandridis, E. Chondrodima, and H. Sarimveis, "Radial basis function network training using a nonsymmetric partition of the input space and particle swarm optimization," *Neural Networks and Learning Systems, IEEE Transactions on*, vol. 24, no. 2, pp. 219–230, 2013.

[25] M. Partovibakhsh and G. Liu, "Online estimation of model parameters and state-of-charge of lithium-ion battery using unscented kalman filter," in *American Control Conference (ACC), 2012*. IEEE, 2012, pp. 3962–3967.

[26] L. Juang, P. Kollmeyer, T. Jahns, and R. Lorenz, "Improved nonlinear model for electrode voltage x2013;current relationship for more consistent online battery system identification," *Industry Applications, IEEE Transactions on*, vol. 49, no. 3, pp. 1480–1488, 2013.