International Journal of Scientific & Engineering Research Volume 13, Issue 12, December-2022
ISSN 2229-5518

Determination of Output Voltage of Li-FePO4 Battery Cells Using Artificial Neural Networks Under Variable Current Profile

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Abstract— The duties of Li-ion batteries in the usage areas are increasing their importance day by day. Various Li-ion battery units are used in strategic systems in the defense industry, space industry, automotive industry, energy usage areas and biomedical areas. In addition, the current demanded by these systems from the power supply is not always constant and changes dynamically. Therefore, it is clear that conducting studies on battery cells and battery units in the electrochemical structure of Li-FePO4, one of the Li-ion battery derivatives that come to the fore with its reliability, with current methods will guide new research areas. In this study, experimental dynamic charge/discharge data on A123 Systems ANR26650 Li-FePO4 battery cells have been investigated. Non-linear current, voltage, and state of charge information are transferred to the artificial neural network method. It is aimed to estimate the output voltage, which is one of the important parameters, with the highest accuracy by following the irregular current profiles and changing state of charge values. Algorithms in the internal structures of artificial neural networks are also compared with each other and a consistent method is determined with the help of statistical error types. The actual error values of the results, the squares of the errors, the mean values of the squares of the errors, and the correlation coefficient are determined and the method of the study is interpreted.

Index Terms— Estimation, Li-FePO4, parameter, neural networks

1 Introduction

IN industrial applications, the current demanded by the systems from the power supply is often not constant. It is known that especially electric vehicles have a dynamic current profile during driving. The user load profile in energy storage systems is also similar [1]. In order to transfer the information of battery blocks that provide energy to systems with dynamic current profile to simulation and testing processes, it is necessary to model with stable methods or to make parameter estimations. Generally, in battery technology types used in energy storage units, the charge rate is lower than the discharge rate [2]. Therefore, the dynamic variation of the charge/discharge current during the specified test periods makes the estimation of the current and voltage profiles more complicated than the operations with constant current. To obtain stable results, it is important to overcome the complexity of the processes by choosing the most accurate methods in parameter estimation. In this direction, methods such as artificial intelligence (AI), artificial neural networks (ANN), and deep learning (DL), which are supported by up-to-date technological developments, are applied to different scientific fields. In optimization-based studies in Li-ion battery technologies, basic heuristic methods such as genetic algorithm and particle swarm optimization are generally preferred [3]. The artificial bee colony (ABC) algorithm, which is one of the new methods, has been adapted to these systems recently [4]. The transfer of the ANN method to this Li-FePO4-based study is also important in terms of contributing to the literature.

The service life of Li-ion batteries varies according to the environmental conditions in which they are used and the charge/discharge profile [5]. Lithium batteries are designed in different electrochemical types due to their advantages and disadvantages such as price, performance, reliability, and cycle life. One of the most advantageous in terms of production cost and reliability is the Li-FePO4 chemistry type [6]. Li-FePO4 battery cells generally have a voltage range of 3.5-2.5 (nominal 3.2-3.3 V), energy density of 120-150 Wh/L, specific energy amount of 80-90 Wh/kg, specific power of 200-300 W/kg, 1500-2000 cycle life [7].

The parts of this study can be summarized as follows: In Section 2, information is given about the ANN method used in the study. Experimental test data and ANN results are compared in Section 3. In addition, the internal algorithms in the ANN are also compared with each other. As a result of the comparisons, the performance of the ANN is commented on by considering the error-based statistical methods. Section 4 summarizes the results at the conclusion of the study.

2 Artificial Neural Network

Inspired by the neurological communication between the body and the brain, ANN sees the functioning of the human brain as a guide. Intercellular communication in the body is provided by neurons. The neurons shown in Fig. 1 are divided into four parts in terms of their anatomical structure: nucleus (core), axon, dendrite, and synapse [8, 9]. The data transmitted to the nucleus, which is the data processing center, through dendrites, is transferred to the axon after the nucleus. Data from the axon are transmitted to other neurons by means of electro-neurological signals. Similar to biological neural networks, ANN contains nerve cells [10, 11]. ANN and brain have fundamental similarities: ANN accesses information by training, neurons seen as weights are responsible for storing information [12].

In the fundamental ANN method given in Fig. 2, communication is provided by systemic neurons. In ANN, besides the input and output data, there are different number of layers between these two stations. When the literature is examined, it is seen that there is no definite agreement on the number of neurons in the hidden layers of ANNs. In addition, the number of neurons is not clear because the subject studied, the method used, and the desired outputs differ in the studies. Therefore, the number of neurons is determined by trial and error [10]. ANNs, which have the ability to learn nonlinear relationships between variables in the objective function, are widely preferred in many areas such as optimization, clustering, estimation, classification, and simulation [13]. In the estimation studies in the literature with ANN, comparisons are made by making error-based performance measurements such as R2, RMSE, MSE, MAE, MAPE (%) between the results and the actual values.

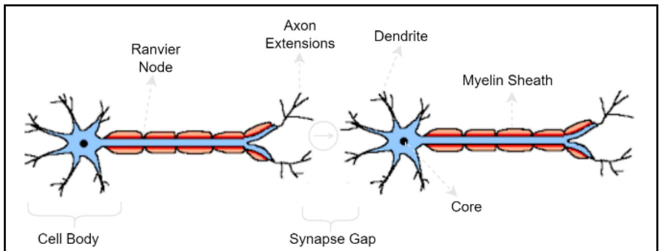

Fig. 1. Biological neuron structure.

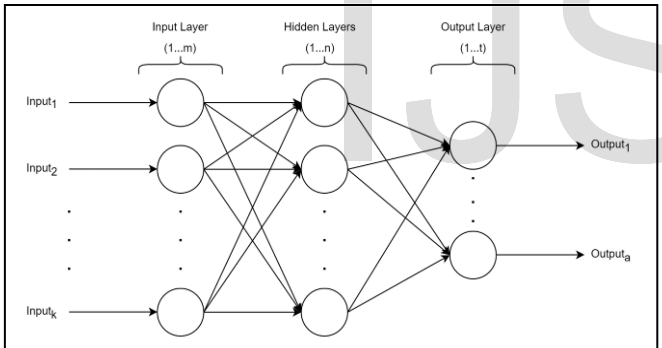

Fig. 2. Neuron structure of ANN.

3 Detection of Dynamic Voltage Profile Using Artificial Neural Network

In cases where there is no possibility of experimental testing of battery cells, it can be used by obtaining the desired data from reliable data banks [14, 15]. The data examined in this study have been taken from the CALCE Battery Research Group database [16-18]. Dynamic cell voltage (VT), dynamic current profile (I) and state of charge (SoC) change for A123 Systems ANR 26650 Li-FePO4 2500 mAh electrochemical battery cell are given in Fig. 3 and Fig. 4.

When the simulation study is performed with the curve fitting (CF) method, it is seen that the most consistent cases provide an average of 65% regression coefficient in the estimation of only current-dependent voltage situations. When the 5th degree polynomial equation is established depending on the value of I and SoC, it is seen that the most consistent cases provide an average of 96% regression coefficient as seen in Fig. 5. However, increasing the number of variables and the degree of equations has a detrimental effect on the stability of the system. This situation necessitates the application of different methods that can be stable.

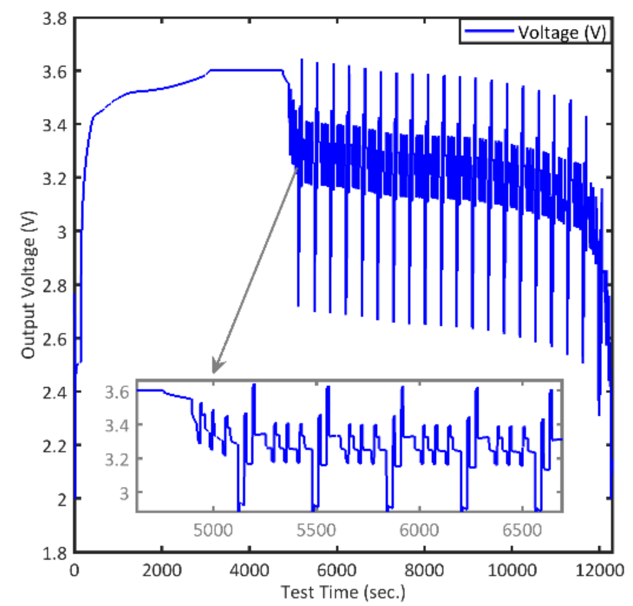

Fig. 3. Experimental actual values of VT change.

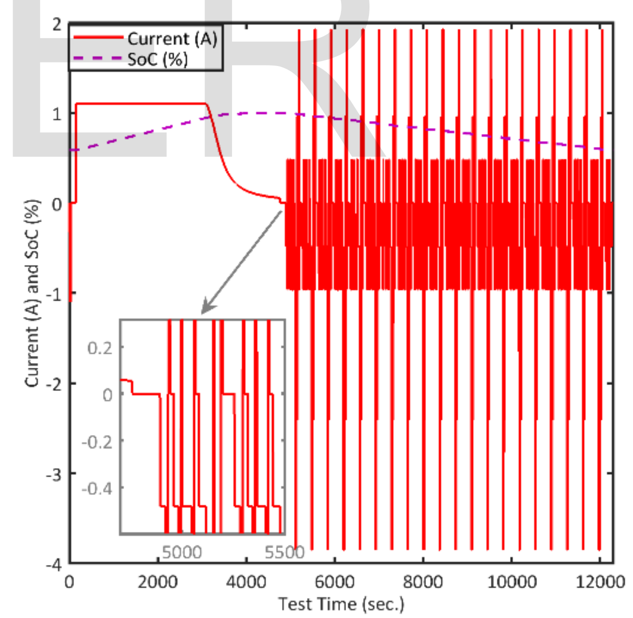

Fig. 4. Experimental actual values of I and SoC change.

As seen in Table 1, Table 2, and Table 3, three different training algorithms in the internal structure of the network have been used in the simulation studies with ANN. Among these internal algorithms, Levenberg-Marquardt is fast, but requires large memory size. The training of the algorithm automatically ends when the simulation study stops developing. In Bayesian Regularization, more time is needed for iterations. It can be a good classification choice for small size data with high complexity and noise level. Training is stopped according to adaptive weight minimization. The Scaled Conjugate Gradient algorithm requires less memory for training. Similar to Levenberg-Marquardt, training of the algorithm automatically ends when the simulation study stops developing. In this study, the training rate is 70%, the validation rate is 15%, the testing rate is 15%, and the number of training is 10.

When the training conditions in Table 1 are examined, the two best performances are exhibited by Bayesian Regularization with 20 neurons and Bayesian Regularization with 30 neurons. Levenberg-Marquardt with 30 neurons has performed close to the first two performances. When the validation situations in Table 2 are examined, although Bayesian Regularization exhibits the best two performances, a random relationship has been observed between the data in the case of correlation.

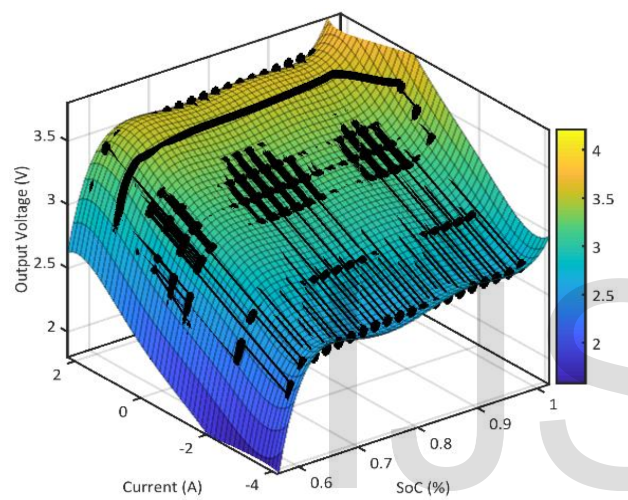

Fig. 5. Simulation study with CF method (Regression coefficient 96%).

TABLE 1
TRAINING PERFORMANCE OF ANN INTERNAL ALGORITHMS

	Training Algorithm	Number of Hidden Neurons	MSE	Regression R Values
Training	Levenberg-Marquardt	10	$(4.9624)10^{-4}$	0.9948
	Bayesian Regularization	10	$(4.4384)10^{-4}$	0.9955
	Scaled Conjugate Gradient	10	$(2.8565)10^{-3}$	0.9711
	Levenberg-Marquardt	20	$(8.0438)10^{-4}$	0.9920
	Bayesian Regularization	20	$(1.7517)10^{-4}$	0.9982
	Scaled Conjugate Gradient	20	$(1.8340)10^{-3}$	0.9814
	Levenberg-Marquardt	30	$(2.4098)10^{-4}$	0.9975
	Bayesian Regularization	30	$(1.7715)10^{-4}$	0.9981
	Scaled Conjugate Gradient	30	$(2.6156)10^{-3}$	0.9732

TABLE 2
VALIDATION PERFORMANCE OF ANN INTERNAL ALGORITHMS

	Training Algorithm	Number of Hidden Neurons	MSE	Regression R Values
Validation	Levenberg-Marquardt	10	$(3.5026)10^{-4}$	0.9969
	Bayesian Regularization	10	0	0
	Scaled Conjugate Gradient	10	$(2.1924)10^{-3}$	0.9767
	Levenberg-Marquardt	20	$(8.5410)10^{-4}$	0.9913
	Bayesian Regularization	20	0	0
	Scaled Conjugate Gradient	20	$(1.4427)10^{-3}$	0.9859
	Levenberg-Marquardt	30	$(2.1024)10^{-4}$	0.9978
	Bayesian Regularization	30	0	0
	Scaled Conjugate Gradient	30	$(2.4806)10^{-3}$	0.9753

TABLE 3
TESTING PERFORMANCE OF ANN INTERNAL ALGORITHMS

	Training Algorithm	Number of Hidden Neurons	MSE	Regression R Values
Testing	Levenberg-Marquardt	10	$(3.6334)10^{-4}$	0.9964
	Bayesian Regularization	10	$(7.1956)10^{-4}$	0.9928
	Scaled Conjugate Gradient	10	$(2.6682)10^{-3}$	0.9727
	Levenberg-Marquardt	20	$(7.7995)10^{-4}$	0.9914
	Bayesian Regularization	20	$(2.6748)10^{-4}$	0.9973
	Scaled Conjugate Gradient	20	$(1.4582)10^{-3}$	0.9848
	Levenberg-Marquardt	30	$(1.2692)10^{-4}$	0.9988
	Bayesian Regularization	30	$(4.9960)10^{-4}$	0.9954
	Scaled Conjugate Gradient	30	$(2.8038)10^{-3}$	0.9719

Levenberg-Marquardt with 30 neurons has showed the second best performance in validation. When the test cases in Table 3 are examined, Levenberg-Marquardt with 30 neurons and Bayesian Regularization with 20 neurons have showed the best performance. When the result data of training, validation, and testing situations have been examined, Levenberg-Marquardt with 30 neurons has showed the most successful performance. Therefore, the study continues by considering the output values of this algorithm.

Fig. 6 shows the real data of the VT and the output values of the Levenberg-Marquardt algorithm with 30 neurons in the ANN. In Fig. 7, the actual error values of the relevant algorithm and the squares of the errors are given. In general, the MSE value $(2.1927)10^{-4}$ is and the correlation coefficient is 0.9978, which is quite acceptable.

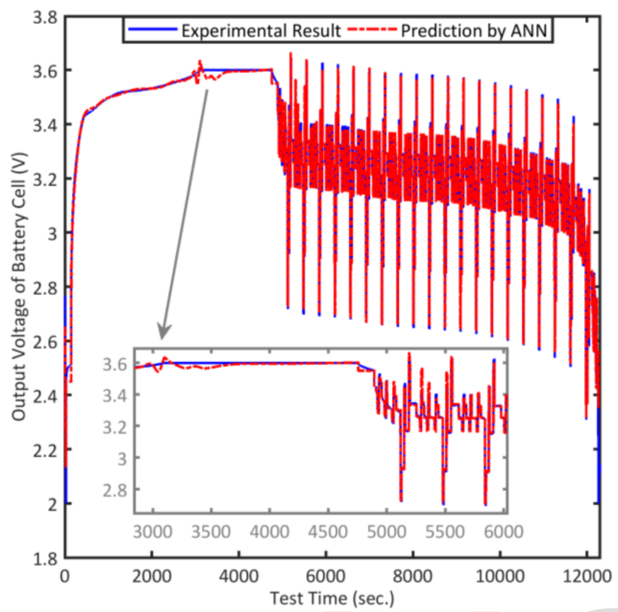

Fig. 6. Actual and estimated values of battery output voltage.

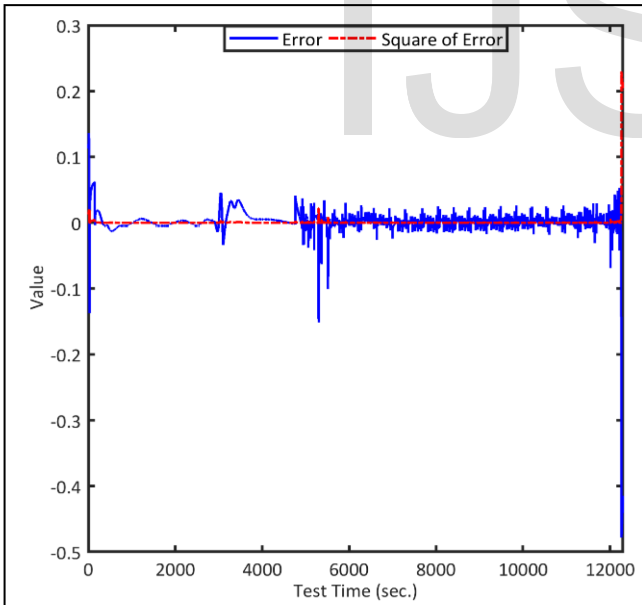

Fig. 7. Error statistics between actual and estimated values of battery output voltage.

4 Conclusions

In the study, which has been carried out using some popular methods, first of all, the artificial neural network has been defined, neurons and layers have been created. Afterwards, the variable current profile, voltage values and state of charge obtained from the experimental test data have been analyzed. By continuing the activities of the study, different training algorithms in the artificial neural network have been combined with different neuron numbers and their performances have been measured. The best performing Levenberg-Marquardt algorithm with 30 neurons has been selected and the estimation process has been started. The error, squares of the errors, and correlation values between the actual data and the estimated data have been determined. As a result, it has been observed that the artificial neural network, which offers high accuracy voltage values even in dynamic current profiles, exhibits consistent and stable behavior. Outputs that have the potential to be transferred to implementation and testing processes have been obtained.

In future studies, it is planned to compare the performances of an optimization algorithm and artificial neural network under three different dynamic flow profiles.

Acknowledgement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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