Measurement of State of Charge of Lithium-Nickel Manganese Cobalt Battery using Artificial Neural Network and NARX Algorithm

Original Scientific Paper

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Abstract *– The battery's SoC is a crucial variable since it reflects its performance. An accurate estimation of SoC protects the battery, prevents overcharging or discharge, and extends its life time. Since most of the traditional methods use complex equations, ANN has been implemented to reduce the complications and provide better accuracy. In this research, Li-NMC with capacity rating of 2000mAh is used for the estimation of SoC. In this paper, Feedforward Neural Network (FNN) algorithm and Nonlinear Auto-Regressive network with exogenous inputs (NARX) have been used for designing a neural network model. Here, the performance matrixes of both neural network models have been compared and analyzed with the same dataset.*

Keywords*:* *ANN, SoC estimation, FNN algorithm, NARX algorithm, Li-NMC battery*

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1. INTRODUCTION

According to European Green Deal, Commission has boosted its rules by setting forth essential policies [1] to attain net-zero global warming emission by 2050. Due to the development of industries, there is a considerable increase of greenhouse effects and emission of carbon [2]. The transportation is biggest source of greenhouse gas emissions globally [3]. As a result, Electric Vehicles (EVs) must be introduced into the transportation industry [4, 5]. In Electric Vehicles (EVs), Lithium-ion battery is mainly used due to its longevity [6]. The life time, safety and charging capability need to be enhanced inorder to improve the performance of the Li-ion battery [7].

The SoC of the battery denotes the available capacity as the function of rated capacity. The value of the SoC varies from 0%-100% [8]. SoC is indirectly assessed using proxies like temperature, potential difference, and capacity [9]. Accurate prediction of SoC is a vital feature in a cell pack utilized in EV's [10]. Electric vehicles require accurate cell SoC prediction for safe and effective operation thereby extending battery life [11]. Estimating battery SoC poses challenges like non-linear battery behavior, model complexity, calibration needs, and limited observability. The research paper covers a literature survey in Section 2, data preparation and collection in Section 3, ANN architecture in Section 4, FNN model in Section 5, NARX model in Section 6, and concludes with results and discussion in Section 7. Section 8 provides the work's conclusion.

2. LITERATURE SURVEY

There is no clear and concise method for calculating the SoC accurately. A Li-ion cell at 100% SoC has all cyclable lithium ions in the negative electrode, while at 0% SoC, they are all in the positive electrode [12].

In [13] the SoC prediction techniques are classified into four groups such as model-based, ampere-hour, open circuit voltage (OCV) and data-driven prediction methods. According to the author [14], the Open Circuit Voltage (OCV) of Li-ion is a critical measure for analyzing changes and estimating the SoC. The charging state slope, measured offline at different temperatures and aging stages, is prone to errors in the OCV-SoC relationship due to operational condition variations [15].

The Ampere-hour is a simple and convenient method used to evaluate the SoC [16]. In [17] the author proposed improved coulomb counting approach with compensation coefficient in order to reduce the error. The author [18] suggested a novel capacity prediction technique on enhanced coulomb counting process and the error is about 1.7%. In [19], the drawback of this SoC calculation method is that a considerable estimation inaccuracy can result from an incorrect initial battery current.

According to the model-based estimation principle, the estimating process cannot manage the inaccuracies from the system model [20]. In [21], the author proposed SoC prediction using HIF and Extended Kalman Filter (EKF). SoC prediction can approximate to the precise value in 30 seconds while maintaining 0.5% efficiency. According to author [22], using Kalman filter incorrect parameters decrease the battery model's accuracy which results in an increase in SoC estimation error. In [23], the author proposed a sliding observer approach that relies on a variable adaptable system model, which had a precision of less than 2%. To provide a rapid prediction model for cell charging state and impedance, a multi-level PI observer is used [24]. In [25] the author suggested a GRU-RNN is used for an accurate SoC estimation. In [26], the author develops a neural network-based BMS (NN-BMS) for a through-the-road hybrid electric vehicle (TtR HEV), with an emphasis on the TtR HEV's recharging capacity. The machine learning approach, which includes Artificial Neural Networks (ANN), is also known as the data-driven approach [27]. An ANN is a mathematical framework made up of a series of independent processing units called neurons that are connected by weights [28].

In this paper, data driven approach (also known as black box model) is used for an accurate SoC prediction. Since this method requires minimum knowledge and time for modeling a system comparing with other methods. The nntool (Neural Network Toolbox) in MATLAB offers a combination of user-friendly interface, extensive functionality, flexibility, integration with other MATLAB tools, and a supportive community, making it advantageous for designing and implementing neural network models. The problem statement includes an accurate estimation of SoC since it is very important factor that should be measured accurately to protect the battery life. Comparison analysis of various SoC measurements is shown in Table 1.

Table 1. Comparison analysis of various SoC measurements

Slno	SoC measurement	Merits	Demerits
1	Circuit based model	Accurately representing physical systems, enabling simulations and versatility.	Accurate parameters are needed, potential simplifications, and limitation to specific types of systems.
2	Neural network model	Parallel processing leads to faster training, adaptability, flexibility, automatic feature learning.	Large data requirements, takes significan-t time for training and lack of transpare-ncy.
3	Pseudo-two-Dimensional(P2D) Model	Computa-tional accuracy, easier parameteridentification.	Assumption and approximtion, simplified geometry, applicatio-n, specific.
4	Single Particle model	Computa-tional efficient, quick sensitivity analysis, conceput-al clarity.	Lack of spatial information, limited applicability to fuel cell, sensitivity to particle size.

3. DATA COLLECTION AND PREPARATION

The input dataset has been gathered from the Battery Research Group of the Center for Advanced Life Cycle Engineering (CALCE) [29]. The feature extraction used in this paper consist of voltage, current, charge capacity, discharge capacity, test time, step time, change in voltage with respect to time (dv/dt), charge energy, discharge energy and internal resistance. Table2 denotes number of sample Data used in Training, Validation and Testing.

Table 2. Data used for training, Validation and Testing

Data	No of Samples
training	11814
validation	3938
testing	3938

4. FEEDFORWARD NEURAL NETWORK (FNN)

A FNN is made up of layers, each of which is made up of neurons. The input layer takes the data to be analyzed and feeds it to one or more hidden layers, that perform the categorization function, before sending it to the output layer [30]. Many neurons make up a FNN, which is also the fundamental unit of information processing [31]. Weights connect each neuron, resulting in probability-weighted correlations among source and result [32]. Fig. 1 shows the architecture of FNN.

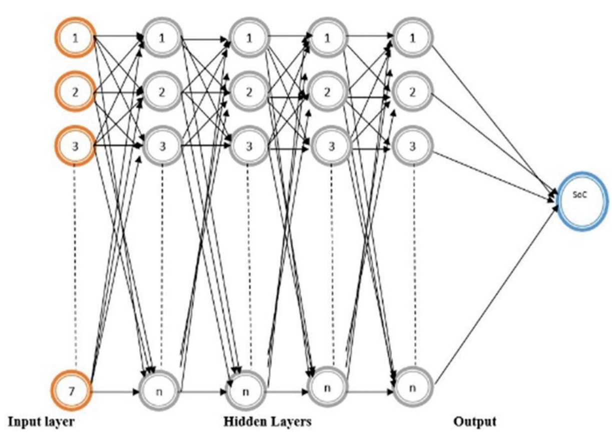

Fig. 1. FNN architecture

Each neuron has activation layer and pre-activation layer. Where, activation layer is denoted as 'h' and spre-activation layer is represented as 'a'. Equation (2) and (3) represents the matrix of the weight 'W_1'and Activation function 'h_1' for first layer respectively. Pre-activation function is 'a_{1n}'for first layer for n neurons.

$$W_1 = \begin{bmatrix} w_{111} & \cdots & w_{11k} \\ \vdots & \ddots & \vdots \\ w_{1j1} & \cdots & w_{1jk} \end{bmatrix} \quad (1)$$

$$h_1 = \begin{matrix} h_{11} \\ h_{12} \\ \vdots \end{matrix} \quad (2)$$

$$= w_1 j_1 x_1 + w_1 j_2 x_2 + w_1 j_3 x_3 + w_1 j_4 x_4 \dots \dots + w_1 j_k b_1 \quad (3)$$

At the output layer 'L,' the activation function is provided by,

$$\hat{y} = f(x) = h_L = o(a_L) \quad (4)$$

Where, o = output activation function.

In this paper, 4-layer FNN has been designed inorder to obtain less MSE. Levenberg-Marquardt learning function and GD transfer function has been used. The reason for choosing GD and Levenberg-Marquardt is fast convergence, adaptive learning rate, simplicity, parallelization and requires less memory compared to more complex optimization algorithms so it is used for large dataset. The computational time is 1000 epochs. The MSE at 1000 Epochs obtained is 1.231e^{-06}. This is the better performance obtained using the proposed FNN model. At 681 epochs, 0.00069379 MSEREG is obtained as better performance using the proposed FNN model. In this, 0.0074991 is obtained as SSE using 1000 Epochs. Comparing with MSE and MSEREG, this SSD error is high.

5. NARX MODEL

The NARX technique improves learning performance and computing efficiency in addressing battery non-linearity. Its predicted output is consistently validated against the true value, enhancing accuracy in time series forecasts by storing both input and previous output values as feedback [33]. Fig. 2 depicts the NARX model architecture.

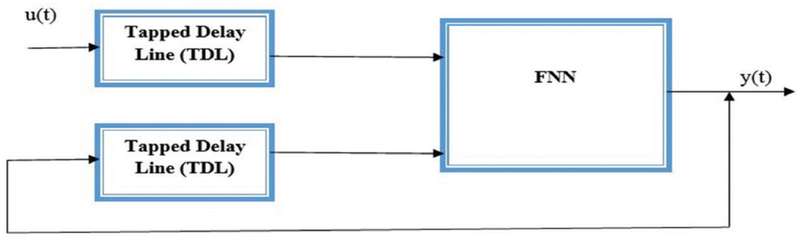

Fig. 2. NARX architecture

The mathematical formula for NARX model provided by the equation 5,

$$y(t) = f(y(t-1), y(t-2), \dots, y(1-n_y), u(t-1), u(t-2), \dots, u(t-n_u)) \quad (5)$$

Where, f= non-linear function, n_u= maximal lags input, n_y= output to the model respectively.

In proposed model, 7 inputs and 1 output are designed. In this model, the result of output layer is given as the feedback to the hidden layer. This feedback makes the difference between FNN model and NARX model. This is done to compare and analyze both model results. The best validation performance of MSE is 9.3021e^{-06}. The best validation performance using MSEREG is 8.2739e^{-05}. The SSE obtained is 0.01233 at 1000 Epochs. Comparing with MSE and MSEREG, SSE error is high. Table 3 shows the best validation performance of FNN and NARX Algorithm for MSE, MSEREG and SSE.

Table 3. Best validation performance of FNN and NARX Algorithm

Performance Matrices	FNN Algorithm	NARX Algorithm
MSE	1.231e^{-06}	9.3021e^{-06}
MSEREG	0.00069379	8.2739e^{-05}
SSE	0.0074991	0.01233

6. RESULTS AND DISCUSSION

To verify the trained models, MSE, MSEREG and SSE have been selected as model's performance indicator. In the fig. 3(a), predicted SoC value of FNN and NARX and actual SoC is plotted with the voltage(V). At initial voltage 3.44V, both the actual and predicted FNN SoC value is 100% while the predicted NARX SoC value is 99%. From 3.44V to 4.19V, the actual and predicted FNN value is 100%. The SoC value of both actual and predicted FNN is reduced from voltage 4.12V to 2.57V and SoC of 32.38% is reached for both actual value and FNN predicted value. The SoC value of NARX gets reduced from the voltage 4.19V to 2.57V and a SoC value of 32.39% is obtained.

In the fig. 3(b), actual, MSEREG predicted FNN and NARX SoC value is plotted with voltage. Initially, both actual and predicted FNN values are 100%, while the NARX prediction stands at 99.99% for an initial voltage of 3.44V. In the voltage range of 3.44V to 4.19V, FNN maintains a 100% SoC. Subsequently, the SoC decreases from 4.12V to 2.57V, reaching 32.38% for both actual and predicted FNN values. For the NARX model, the SoC prediction remains at 99% from 3.44V to 3.52V and reaches 100% from 3.52V to 4.19V. The NARX prediction decreases from 4.12V to 2.57V, resulting in a SoC of 32.40%.

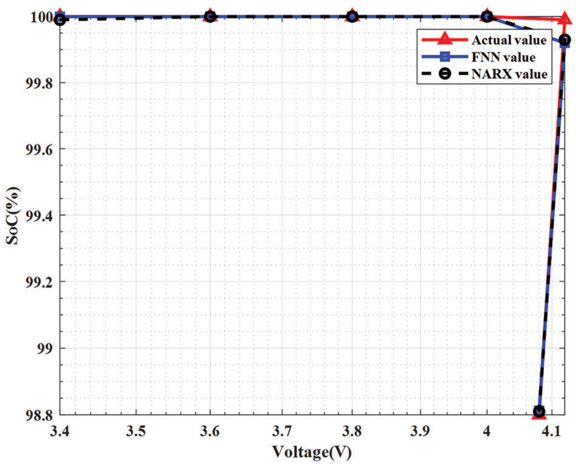

Fig. 3(a). MSE value of FNN, NARX, Actual value Vs Voltage

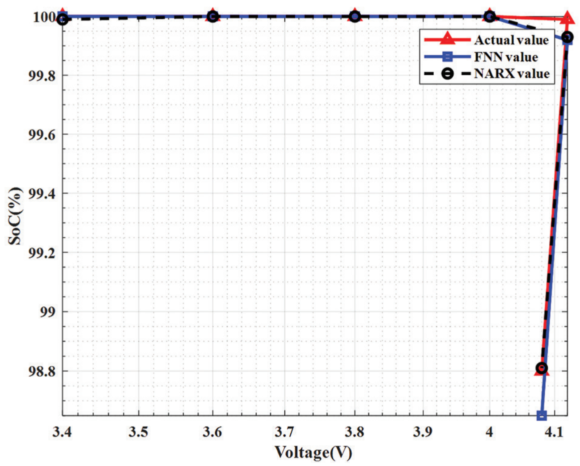

Fig. 3(b). MSEREG value of FNN, NARX, Actual value Vs Voltage

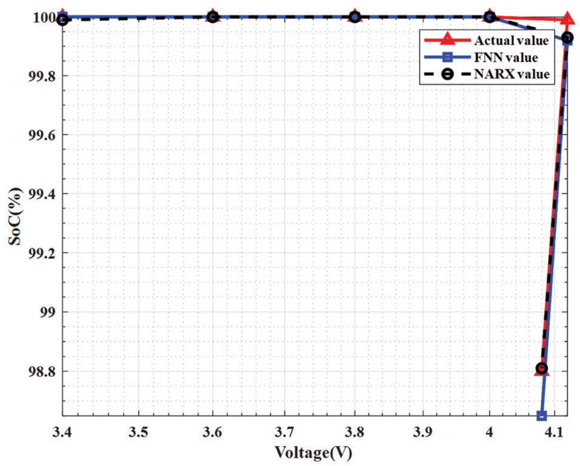

Fig. 3(c). SSE value of FNN, NARX and Actual value Vs Voltage

In the above fig. 3(c), SSE predicted value for FNN & NARX and actual value is plotted with the voltage. At initial voltage 3.44V, both the actual and predicted FNN SoC value is 100% whereas the predicted NARX SoC value is 99%. From the voltage range 3.44V to 4.19V, the actual SoC value is 100%. Whereas from 344V to 4.11V, the predicted FNN value is 100%. NARX SoC of 99% is obtained from the voltage 3.44V to 3.44V. During this period, the current and charge capacity is increased. Finally, SoC of 32.38% is obtained. From 3.44V to 4.19V, the actual SoC value is 100%.

In Fig. 4(a), the actual value, predicted FNN and NARX SoC value is plotted with respect to test time. At initial test time 1.12 seconds, the voltage is 3.44V. From 1.002seconds to 1.25seconds, the actual SoC and FNN value is 100%. However, from time period 1.002 seconds to 64.03 seconds, the NARX value is 99%. At 65.04 seconds, the NARX value is 100%and it is continued till time period 1.22 seconds. The NARX SoC value begin to reduce from 12293.32 seconds to 1.98 seconds and SoC value of 32.39% is obtained. From 1.12 seconds to 1.25 seconds, the actual & FNN value is of 100% while from 1.25 seconds to 1.98 seconds, the actual & FNN value is reduced and 32.38% of SoC is obtained.

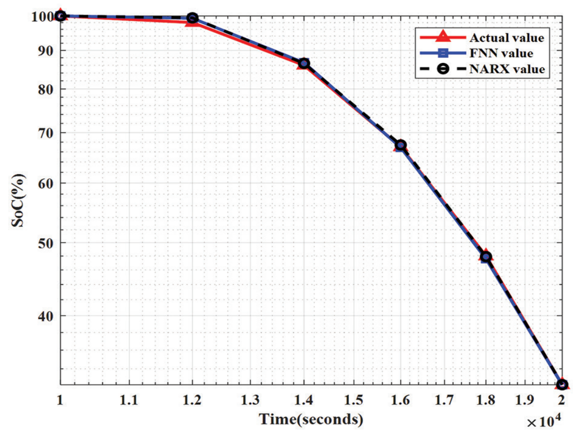

Fig. 4(a). MSE value of FNN, NARX and Actual SoC value Vs Test time

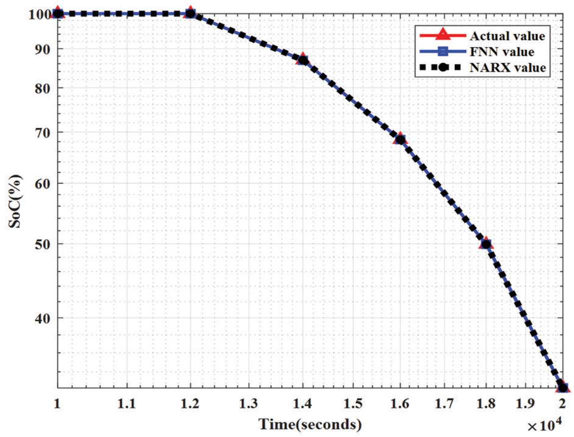

Fig. 4(b). MSEREG value of FNN, NARX and Actual SoC value Vs Test time

In Fig. 4(b), the actual, predicted FNN and NARX SoC value is plotted with respect to test time. At initial test time 1.002 seconds, the actual & predicted FNN SoC is 100% and NARX value is 99%. From 1.002 seconds to 1.25 seconds, the actual & FNN value is 100%. In NARX, the SoC value is 99% from 1.002 seconds to 60.00 seconds. From 61.0017seconds to 1.25.15seconds, the NARX SoC value is 100%. During this time period, the current is 0A. From 1.25seconds to 1.98seconds, the actual & FNN SoC value is reduced and 32.38% is obtained. From the time period 1.25seconds to 1.98seconds, the NARX value is reduced and SoC of 32.40% is obtained. From 1.07seconds to 1.25seconds, the current reaches 0A whereas the current value gets reversed from the time period 1.25seconds to 1.98seconds.

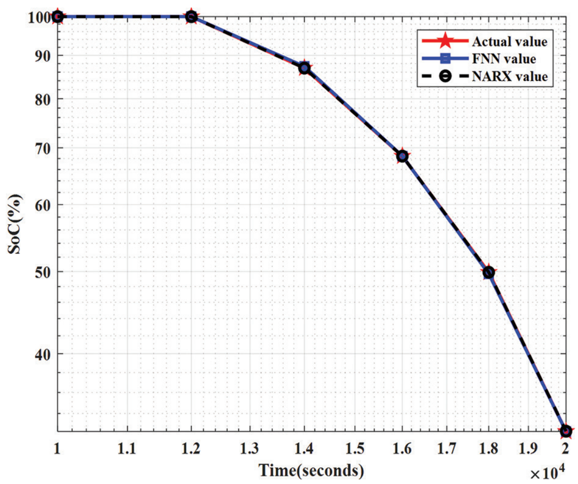

Fig. 4(c). SSE value of FNN, NARX and Actual SoC value Vs Test time

In the above Fig. 4(c), the actual value, predicted FNN and NARX SoC value is plotted with the test time. At initial time period 1.002 sec, both actual and predicted FNN SoC value is 100%. Whereas, NARX SoC value is 99.9%. From the time period 1.002166seconds to 12593.15seconds, the actual SoC value is 100%. This actual value decreases from 1.25 to 1.98seconds and SoC of 32.38% is obtained. From 1.002166seconds to 1.26seconds, the predicted FNN value is 100%. This value starts decreasing from the time period 1.26seconds to 1.98seconds and SoC of 32.38% is obtained. Similarly, from the time period 1.002 seconds to 64.03 seconds, the NARX value is 99%. From 65.04 seconds to 1.25seconds, the SoC value is 100%. This SoC value of NARX begins to reduce from 1.25seconds to 1.98seconds and 32.38% is obtained.

Table 4 shows comparison table based on different neural network algorithm with the existing model. In this table, most of the algorithms are compared with respect to performance matrices and input parameters. Considering MSE value, FNN model has better performance accuracy while NARX is less comparing with FNN model. In MSEREG and SSE, NARX model has better accuracy than FNN model. Even though nntool provide accurate estimation it has some limitations such as dependency on MATLAB (i.e it works on MATLAB platform alone), slow code execution, limited scalability, lack of advanced deep learning features.

Table 4. Error comparison of different Neural Network Algorithms.

Algorithm	Training function/learning Function/Transfer function	Input parameter	Error Rate
Multilayer Perceptron [34]	Levenberg Marquardt/ Gradient Descent/Hyperbolic Tangent Sigmoid	Time, Current, Voltage	3.11×10^{-6}
Feed forward [35]	Gradient Descent/ sigmoid activation function.	Current, voltage	>1%
Feed forward [36]	Gradient Descent	Current, voltage, time	>2%
feed-forward [37]	Levenberg–Marquardt,	Current, voltage	0.025
LSTM [38]	Levenberg–Marquardt	Current, voltage, temperature	>2%
LSTM-RNN [39]	-	Voltage, current	2.088%MSE 2.44% RMSE
FNN and NARX	Levenberg–Marquardt/GD	Current, voltage, charge capacity, discharge capacity, dv/dt, DOD, test time	FNN=$1.231e^{-06}$ MSE, 0.00069379 MSEREG, 0.0074991 SSE NARX=$9.3021e^{-06}$ MSE, $8.2739\ e^{-05}$ MSEREG, 0.01233 SSE

7. CONCLUSION

In this paper, a 4-layer FNN and recurrent NARX neural network have been designed and sigmoid is used as activation function. The performance matrix MSE of FNN is found to be $1.231e^{-06}$ and NARX is $9.3021e^{-06}$. Similarly, MSEREG and SSE of NARX model has better accuracy than FNN model. Finally, an accurate performance indicator for SOC prediction of Li-NMC battery has been found employing nntool MATLAB2021b. The future work is to design a neural network with many numbers of neurons and hidden layers. Different type of batteries can be trained and a comparative study can be done with respect to performance matrices.

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