International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I7P218
Volume 70 Issue 7, 169-179, July 2022

Review Article

Comprehensive Review on State of Charge Estimation in Battery Management System

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Received: 09 May 2022 Revised: 30 June 2022 Accepted: 12 July 2022 Published: 20 July 2022

***Abstract** - This paper describes the latest methods and enhanced techniques used to determine the precise State of Charge (SOC). The three primary factors influencing SOC accuracy are the environmental temperature, current, and open-circuit voltage for a typical battery. It is essential to know the SOC that judges the battery's life. This paper analyzes five different methods to estimate the SOC using different Algorithms and Neural networks. These methods are state-of-the-art methods that can be used to check the correctness of the measurement of SOC in batteries. This paper discusses and analyses the Regression algorithm, time series algorithm, K nearest neighbor algorithm, AGA-based RBF neural network, and Back Propagation neural network to determine the précised SOC. Each method's advantages and disadvantages were discussed and compared with other models to show their superiority. A sample of data was fed to these models, and the result was noted for all five methods. Later, the data were analyzed for their accuracy.*

***Keywords** - AGA-based RBF neural network, Backpropagation neural network, K nearest neighbor algorithm, Regression algorithm, State of charge, Time series algorithm.*

1. Introduction

The government recommends using electric vehicles to avoid environmental pollution and the fossil fuel crisis[1]. These environmentally friendly vehicles do not depend on fossil fuels[2]. These vehicles use batteries to function. Off-late, many companies are investing in manufacturing electric vehicles. These include two-wheelers and Four-Wheeler. Few companies have already manufactured and sold these vehicles to users. However, they fine-tun the batteries for their long-lasting mileage[3]. The main component of electric vehicles is batteries. In the overcharged battery of an electric vehicle, the electrolyte inside the battery gets heated, and the battery's temperature increases for a long time which may cause a fire. If an over-voltage/over-current occurs during cell balancing, a power surge could be inside the battery, leading to a breakdown. So, it is important to take care of the batteries from over-charging, under-charging, over current, under-voltage, short circuit, and temperature variations so that it gives long life to the batteries[4]. The Battery Management System (BMS) helps monitor the battery packs, charge status, and health status and helps optimize the battery. Cell balancing technology will improve the battery's life for a long time. The Battery Management System (BMS) helps monitor the battery packs, charge status, and health status and helps optimize the battery. Monitoring voltage, temperature parameters, and coolant flow are achieved thru BMS. The components of BMS are as shown in Fig. 1.

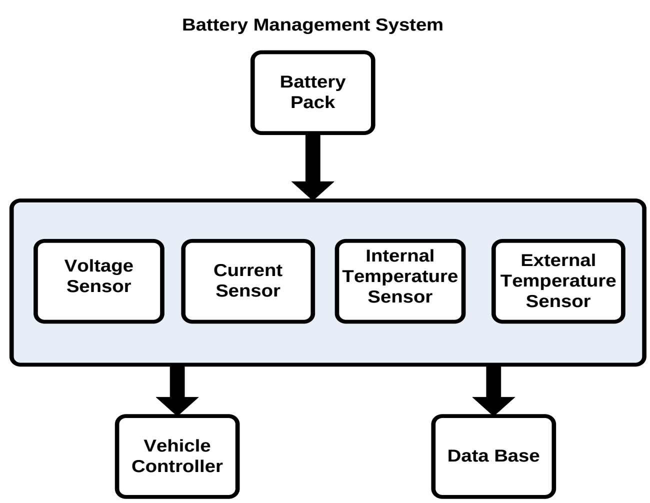

Fig. 1 Components of BMS

1.1. Components of BMS

1.1.1. Obtain temperature data from the battery

- To measure a precise temperature inside the battery is challenging. If the accurate temperature of the battery is not measured, the battery life is decreased. Hence, sensors are used to measure the temperature[5].

- Both environmental and internal battery temperatures are necessary to evaluate the battery's health.
- The temperature must be measured at charging, discharging, and storage.

1.1.2. Obtain voltage data from the battery

- It is essential to measure the battery's voltage to estimate the battery's SOC and State of Health (SOH).
- The SOC and SOH of the battery mainly depend upon the voltage inside the battery.If there is a millivolt variation in the voltage measurement, there will be a massive difference in the battery's SOC calculation. So, it is necessary to use an accurate sensor to measure the voltage, which has high precision.

1.1.3. Obtain current data from the battery

- It is necessary to measure the current flowing in the battery during charging and discharging.
- It is also necessary to calculate the SOC and SOH of the battery.
- To measure the power, the voltage, and current data are considered to evaluate the power consumed during charging and dissipated during discharging [6].
- Hall effect sensors are used to measure the current.

1.1.4. Communication

- After collecting the data, BMS will forward the data to the vehicle controller and a remote device[7].
- The IoT (Internet of Things) device is installed in the vehicle controller. If BMS observes any fault, it will isolate the circuit via the IoT device[8].
- BMS will also send the data to the remote device, where-in analysts would be monitoring the data sent by BMS[9].

1.2. State of Charge

The most crucial parameters for batteries are SOC [8]. SOC is defined as the ratio of the quantity of energy remaining at the time of measurement in the battery to the quantity of energy when it was new, as shown in the formula. A complete charged battery has a SOC of 100 percent, while a complete discharged battery has a SOC of 0 percent[11].

$$SOC=\frac{\text{Battery residual AH}}{\text{Battery nominal AH}} \tag{1}$$

The accurate measurement of SOC helps to predict the safety of power batteries. The measurement of SOC solely depends upon the cell voltage. SOC depends on the reaction of electro-chemical in the battery cell, which is primarily nonlinear and depends on the operating temperature, current, and voltage parameters. Consequently, it varies with the vehicle's driving condition, like vehicle speed[12].

Fig. 2 shows the characteristics of SOC.

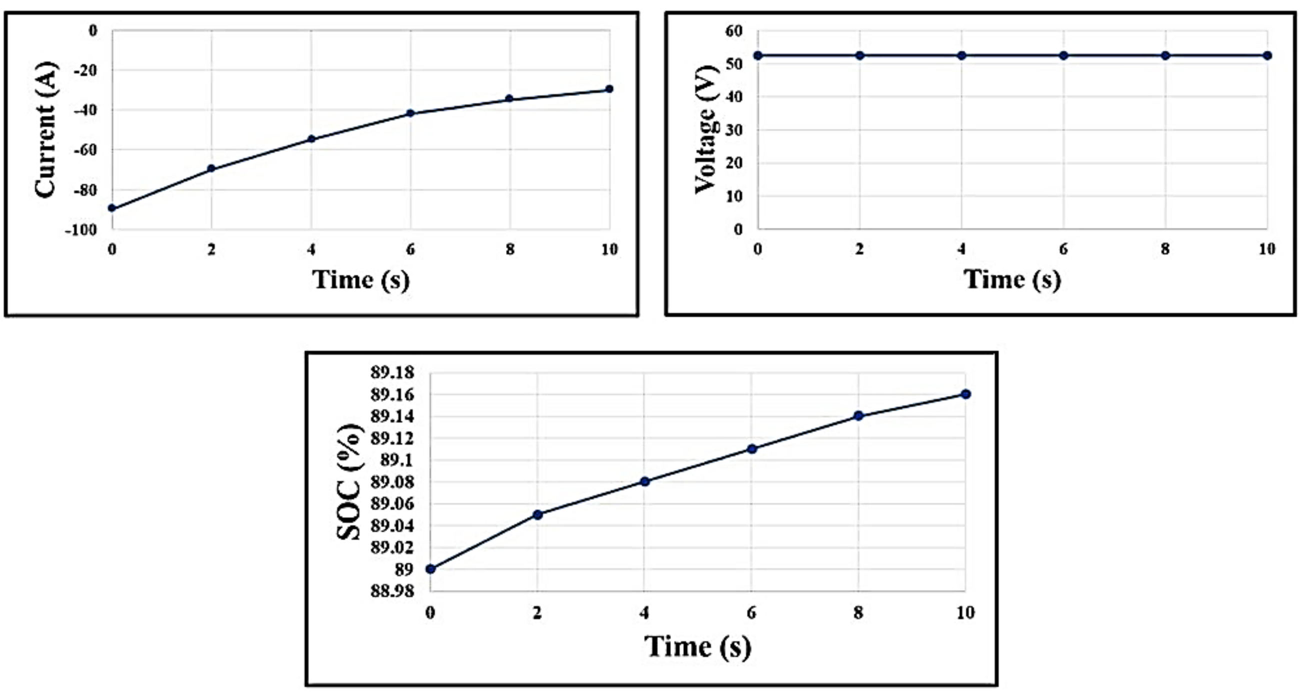

Fig. 2 Current, Voltage, and SOC Characteristics

Numerous approaches have been developed to estimate SOC. However, coulomb counting is the most common method to estimate SOC [13]. In this method, the current is integrated over time to measure SOC. The main drawback of using this method is that the measurement and calculation errors appear due to the integration function[14]. Therefore, it cannot predict accurate SOC[15]. The SOC lookup table is used by the voltage-based method to estimate SOC. This method does not work well because there are no variations in the discharge characteristics. Research is going on to make the SOC battery model a data-driven module. Deep learning and neural networks are commonly used data-driven modules [16]. This paper discusses the Regression algorithm, Time series algorithm, K nearest neighbor algorithm, Accelerated Gradient Algorithm (AGA) based on Radial Basis Function (RBF) neural network, and Backpropagation neural network to estimate the SOC of a particular battery[17] [18].

2. Determination of SOC

The following algorithms are used to determine the SOC.

1. Regression model
2. Time Series algorithm
3. K nearest neighbor algorithm
4. AGA-based RBF neural network
5. Back Propagation neural network

2.1. Regression Model

This algorithm plots the graph between the dependent and independent variables. It predicts the dependent variable's future behavior based on the independent variable's assumed influence [19].

Table 1. Regression Model Data Set

Voltage	Temperature
200	20
250	22
300	30
350	32
400	38
450	40
500	45

To explain this model, the considered sample values of voltage and temperature as shown in Table 1. This analysis was derived with the help of Microsoft-Excel. In Microsoft-Excel, the data analysis tool was activated, and a particular data was entered in the excel sheet, and the data was selected to execute the regression analysis[20]. The results are shown in Fig. 3.

where,

Multiple R - This value tells how strong the LINEAR relationship is.

R Square - It is the co-efficient of Determination. It tells us how much variance the independent variable can account for the dependent variables. The temperature measures can account for 98 percent of the variance in voltage.

Standard Error - The standard linear straight line indicates a stable temperature. However, if the temperature distance is from the stable temperature, it is called the standard error.

Adjusted R square-It is the updated version of R-square that has been adjusted for the number of predictors in the model.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.990292215
R Square	0.98067867
Adjusted R Square	0.976814404
Standard Error	1.411685922
Observations	7

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	505.75	505.75	253.781	1.77416E-05
Residual	5	9.9642857	1.99286		
Total	6	515.71429			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	2.678571429	1.9422137	1.37913	0.22635	-2.314047711	7.67119	-2.314	7.67119
X Variable 1	0.085	0.0053357	15.9305	1.8E-05	0.07128422	0.09872	0.07128	0.09872

Fig. 3 Regression Statistics

The average distance is when the observed value drops from the Regression line. This value indicates how much error will be there in the assumed temperature concerning voltage.

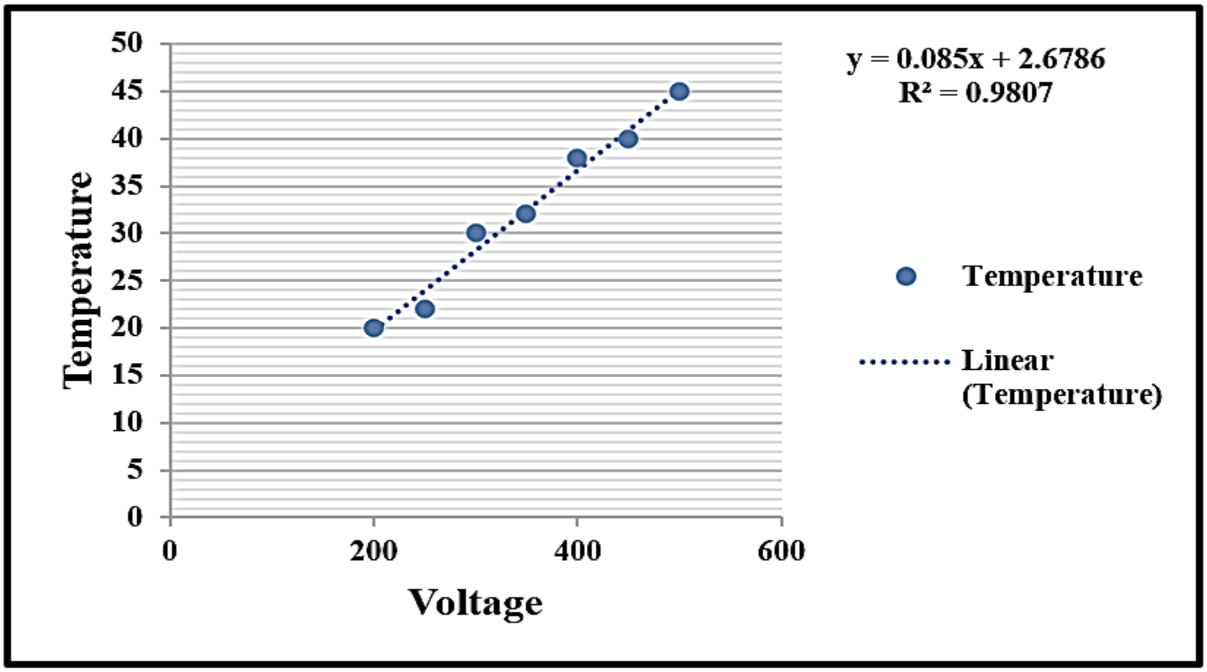

Fig. 4 Voltage Vs. Temperature

Fig. 4 is the plot of voltage and temperature. The dotted linear line represents the linear relationship of the temperature with voltage, and the regression values will be almost linear. The regression model for the data will compare voltage against the given temperature and give the approximate temperature value with + or - Standard Error as per the regression table. For example, if the voltage value is not in the reference value, it will calculate the nearest value to match the temperature. If the voltage value is 225, which is not in the reference data, the regression model will calculate the approximate temperature as 21degrees based on the reference. This value will have an error of ± 1.411 percent. In this way, it is easy to analyze the battery's temperature in an electric vehicle to monitor its health.

2.2. Time Series Algorithm

This algorithm predicts the next day's value by using previous values of voltage, current, and temperature. To demonstrate this algorithm, the temperature data recorded for the past ten days are shown in Table 2 [19].

Table 2. Time Series Algorithm Data Set

Date	Temperature
1	20
2	22
3	30
4	25
5	34
6	30
7	20
8	22
9	20
10	26

The data is entered in excel to predict the next three days' value. Using the forecast sheet option in excel, the data was analyzed. The results are as shown in Fig. 5.

Date	Temperature	Forecast (Temperature)	Lower Confidence Bound (Temperature)	Upper Confidence Bound (Temperature)
1	20			
2	22			
3	30			
4	25			
5	34			
6	30			
7	20			
8	22			
9	20			
10	26	26	26	26.00
11		23.65064366	12.9222028	34.38
12		23.54490014	11.54533687	35.54
13		23.43915662	10.29	36.59

Fig. 5 Results Obtained from Time Series Algorithm

It can be observed from Table 2 that the values given were only for ten days[21]. Fig. 5 shows that the prediction for the next three days is also displayed using the time series algorithm. The maximum and minimum mean temperatures were averaged to predict the temperature for the next three days[22]. Fig. 6 shows the plot for Table 2.

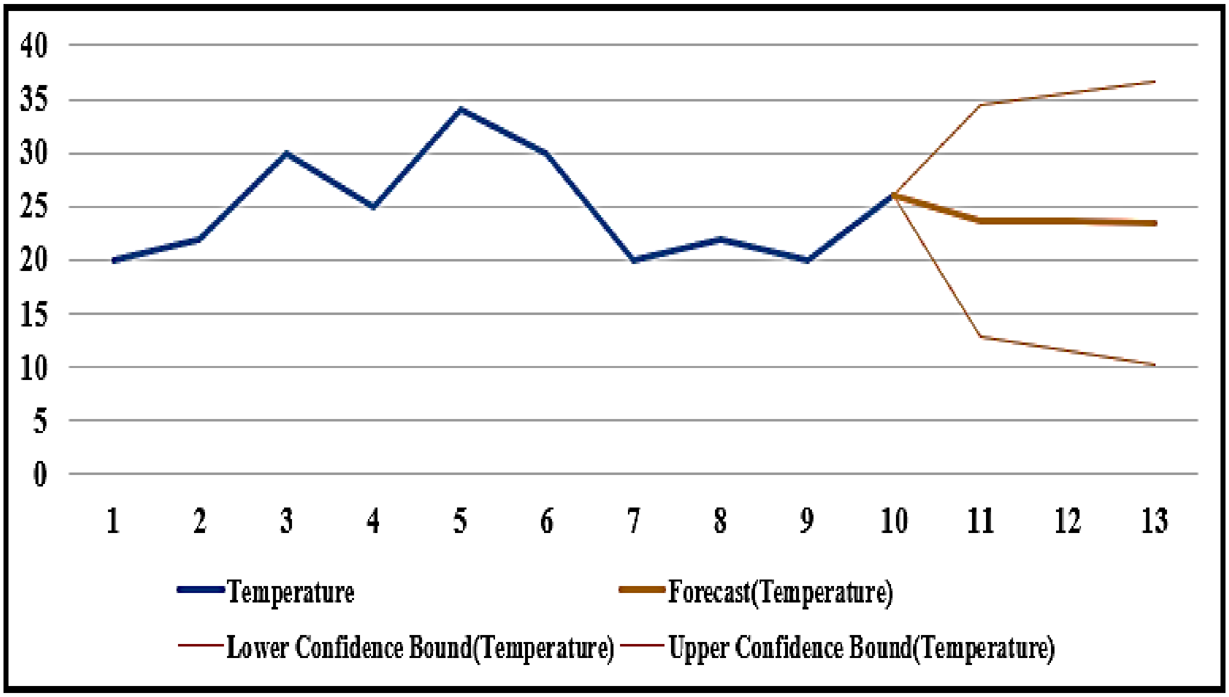

Fig. 6 Plot of Time Series Algorithm

2.3. K Nearest Neighbor Algorithm

The KNN algorithm is used to classify the given data into a specified category. Table 3 represents the sample data considered for demonstrating this algorithm

Table 3. K Nearest Neighbor Algorithm Data Set

Date	Voltage	Temperature	Distance	Rank	Category
1	200	20	320.76	7	1
2	250	22	270.74	6	1
3	300	30	220.33	4	1
4	280	25	240.60	5	1
5	400	34	120.27	2	2
6	500	40	20.10	1	2
7	520	42	0.00	0	2

The voltage and temperature difference is calculated using the formula 2 [23].

$$d = \sqrt{(p_2 - p_1)^2 + \ (q_2 - q_1)^2} \qquad (2)$$

where,

(p_1, q_1) are the coordinates of the first point. (In SOC, it is voltage).

(p_2, q_2) are the coordinates of the second point. (In SOC, it is temperature).

d is the distance between (p_1, q_1) and (p_2, q_2). (In SOC, it is distance).

For simplicity, formula 3 is added in excel, as shown, to make the calculation easy

$$\mathrm{SQRT}\ ((C3 - \$C\$10)2 + (D3 - \$D\$10)2) \qquad (3)$$

The next step is segregating the values based on convenience into two or more different sections. It is segregated based on the value of temperature. If the temperature is >30 degrees, then the plot will be represented with a red point and a blue point[24].

Once the algorithm is completed and inputs a value not present in the reference data, the approximate value will be plotted on the graph. It can be illustrated as shown in Fig. 7 and Fig. 8.

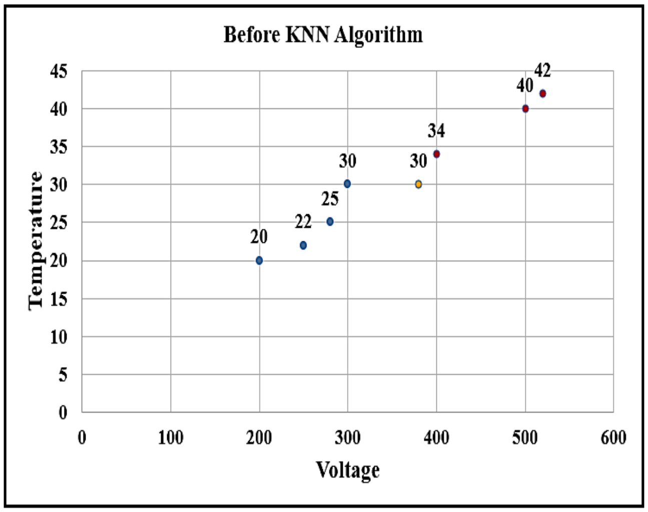

Fig. 7 Before KNN Algorithm

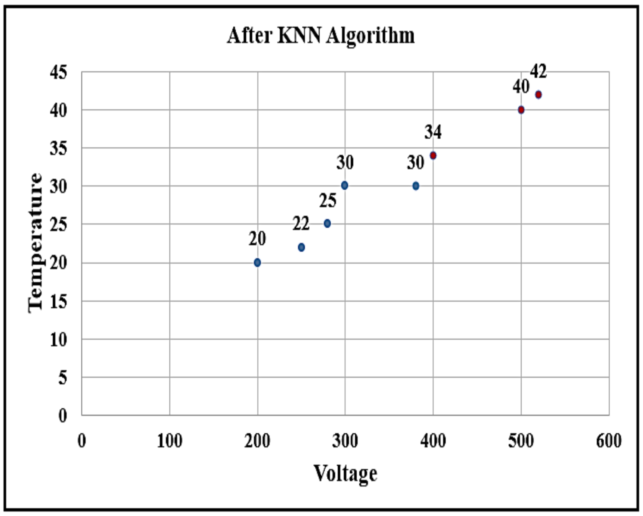

Fig. 8 After KNN Algorithm

A value of 380 volts was chosen at a temperature of 30 degrees on the graph. After applying the KNN algorithm, the yellow point changed to blue. This is how the KNN algorithm works.

2.4. AGA-based RBF neural network

RBF is a type of neural network which consists of the input layer, one hidden layer, and an output layer[25]. It follows a nonlinear mapping to map between input and output layers; the only disadvantage of this neural network is it is difficult to find the number of neurons in the hidden layer for the given input space. So, an AGA algorithm was discovered to determine the number of neurons in the hidden layer. This algorithm involves both RBF and AGA principles; hence, it is called a hybrid topology[26].

AGA working principle

Steps involved by the AGA algorithm include

- It will first create a random set of a population where it considers the set as chromosomes which constitutes the genes.
- The randomly selected chromosomes are made to undergo an evaluation to match the RBF network's standard fitness [27].
- After the test is conducted, it will segregate the number of chromosomes that have satisfied the requirements.
- Now, the chromosomes segregated will be made to exchange the genes within the segregated chromosomes, and a fitness test will be conducted to verify the requirements.
- Transmutation would be done to get the best results.
- Fig. 9 shows the AGA working principle.

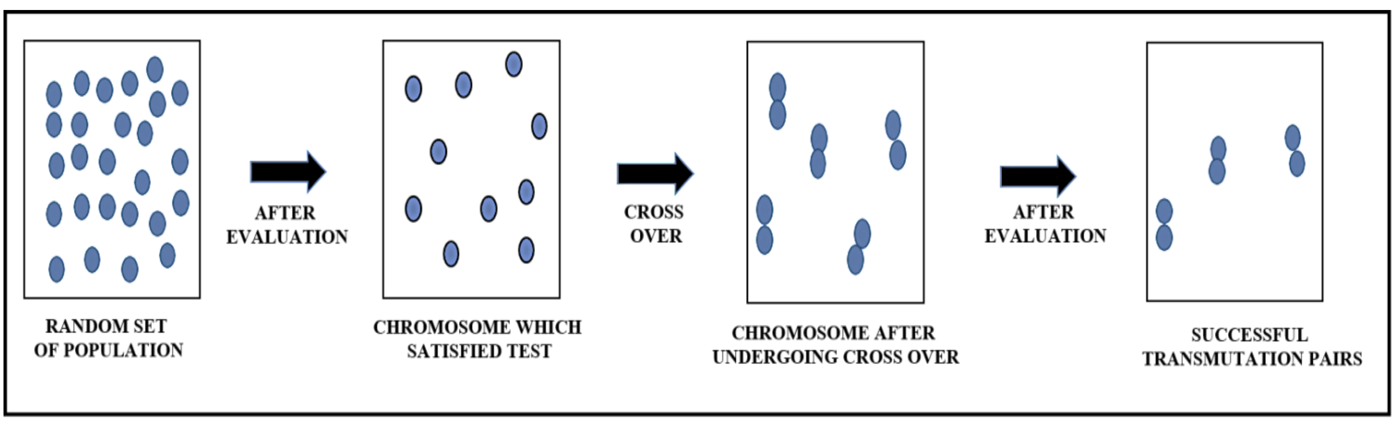

Fig. 9 AGA Working Principle

AGA and RBF working principle

Now, in total, look into the working of the RBF neural network with the AGA algorithm.

- RBF will collect the battery discharge data and store it in a database.
- A training algorithm will be decided and fed to the AGA network.
- The AGA network will now determine the number of hidden nodes and train the network.
- If the error is high, it will make sure to reduce the error and stop the operation.
- Fig. 10 shows the flowchart for this hybrid topology.

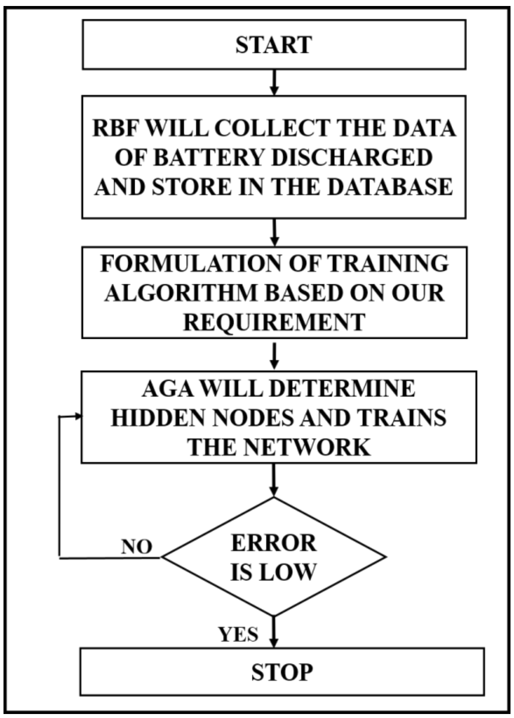

Fig. 10 Flow Chart for AGA-Based RBF Neural Network

2.5. Back Propagation neural network

This type of Artificial Neural Network (ANN) [28] consists of many layers. It consists of three layers mainly:

- Input layer
- One or more hidden layers → weights and biases
- Output layer.

Fig. 11 shows the different layers[29].

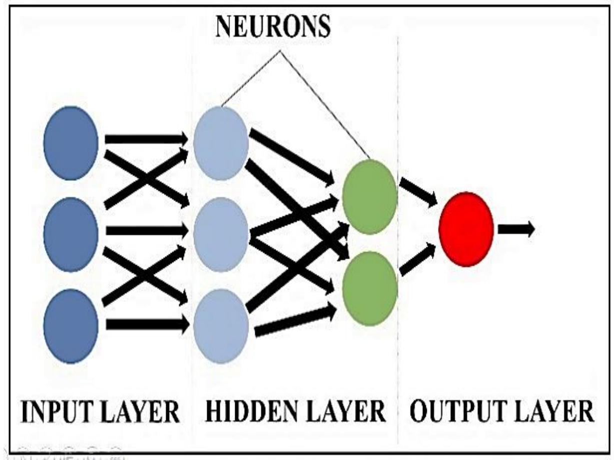

Fig. 11 Back Propagation Neural Network

Once the input is provided, it will go to the hidden layer neurons to check the error in the INPUT, and once there is an insignificant error, the output is given. This cycle is continuous. The error is calculated based on the delta method. The procedures followed in this method are[30]:

- Initialization of Random error

w1 = ran(I,N)
w2 = ran(1,0)

Where,
w1=weight of neuron in between the input and middle layer
w2=weight of the neuron in between hidden and output layer
I is the input
N is the number of neurons

- Calculation of Present Error by formula 4 [31]:

$$\mathrm{error}_t = \mathrm{pred}_t - \mathrm{act}_t \qquad (4)$$

pred_t is the predicted output value
act_t is the actual output obtained

- Total Error

The error is calculated by applying the formula 5 [32]:

$$\mathrm{Err} = \sqrt{\sum_{t=1}^{n}(\mathrm{Error}_t)^2}\sqrt{\sum_{t=1}^{n}(\mathrm{pred}_t - \mathrm{out}_t)^2} \qquad (5)$$

Algorithm to train this model[33]:

- Step 1: Input the data inside the input layer of the BPN network.
- Step 2: Initialize the parameters of the input and hidden output layers.
- Step 3: Formulate a control flow for the model to work to our convenience.
- Step 4: Calculate the error by using equations
- Now the model is ready.

- Once it is instructed to start, it calculates the error. If the error is less than the preset value, it gives the output, or it will go to step number 4[34].

Fig. 12 shows the flow chart for this algorithm.

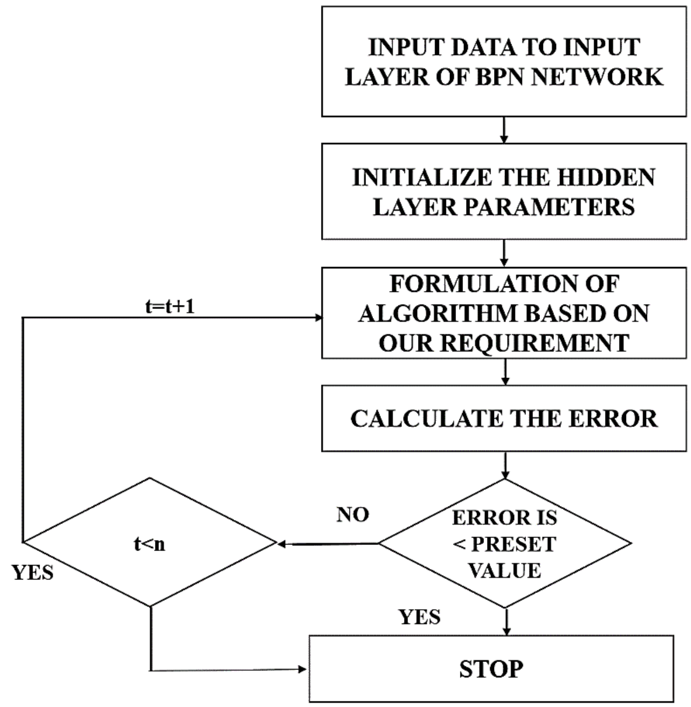

Fig. 12 Flow Chart for Back Propagation Neural Network

3. Comparison Table Between the Characteristics of Different Algorithms

Table 4. Comparison Table I

Regression vs. Time-series vs. k-nearest algorithms vs AGA-based RBF neural network vs. Back Propagation Neural network					
Particulars	**Regression**	**Time Series**	**K Nearest**	**AGA Based RBF Neural Network**	**Back Propagation Neural Network**
Input	I(t), V(t), T(t)	I(t), V(t), T(t)	I(t), V(t), T(t)	I(t), V(t), T(t)	I(t), V(t), T(t)
Output	SOC(t)	SOC(t)	SOC(t)	SOC(t)	SOC(t)
Structure	The Lineargraph between dependent and independent variables[35]	Recurrent neural network with nonlinear autoregressive network[19]	Binary tree[36]	Feed-forward with one hidden layer[26]	Feed-forward with multiple hidden layers[33]
Functions	Based on the Line equation (y=mx+c)[19]	Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing, Seasonal Trend Decomposition[19]	Euclidean distance, Cosine similarity measure, chi-square, correlation[23]	Gaussian function is used[26]	Non linear functionis used[33]
Error Rate	+ or – 2% [19]	+ or – 0.33% [19]	+ or – 6% [37]	Less than or equal to 5% [26]	Less than 0.001%

4. Advantages and Disadvantages of Algorithms

Table 5. Comparison Table II

Algorithms	Advantages	Disadvantages
Regression	• Simple to implement and easier to interpret the output coefficients • Less complexity[38]	• Technique outliers can have huge effects on the regression[38]
Time Series	• High accuracy and simplicity • Reliable decision-making tool[39]	• Errors will be propagated throughout the forecasts if there are many outliers • Does not give the exact value[39]
K-nearest	• It is simple to perform • It requires less time for calculation [40]	• Will generate wrong predictions if feature scaling is not done. • It is sensitive to noise in the dataset[40]
AGA-based RBF	• The training phase is faster as there is no backpropagation learning involved • The network structure is easy as it consists of input, hidden, and output layers. • Neurons in the hidden layers can be determined, and their roles can be easily understood[41].	• Classification is slow in comparison to Multi-layer Perceptron[41]
Backpropagation	• Fast, simple, and easy to program • It is a standard method that usually works well • It is flexible and does not require prior knowledge about the network[42]	• Performance on a specific problem is dependent on the input data[42] • Data mining can be pretty sensitive to noisy data

5. Conclusion

Five algorithms such as Regression, Time-Series, KNN, AGA-Based RBF, and Back Propagation algorithms have been discussed in detail and compared to their traits, advantages, and disadvantages. This paper comprehensively analyzes the different algorithms to determine the SOC of a battery. Though the regression method is simple, it results in significant errors. The time series algorithm leads to inaccurate results by the effect of various factors, so this method sometimes becomes unreliable.

Though the KNN algorithm operates fast, it cannot handle a massive amount of data. Based on the error percentage and disadvantages, the AGA-Based RBF neural network and Back Propagation neural network are recommended methods to determine the SOC of a battery. They are more reliable, and the error percentage is less when compared to all other algorithms. The SOC determined by these two methods is almost accurate, which helps estimate the battery's health. So, these methods can be incorporated into electric vehicles to ensure proper battery working.

References

[1] Uma Ravi Sankar Yalavarthy, Venkata Siva Krishna Rao Gadi, " PEM Fuel Cell Powered Electric Vehicle Propelled By PMSM Using Fuzzy PID Controller- A Research," *International Journal of Engineering Trends and Technology,* Vol.70, No.1, Pp.63-74, 2022.

[2] Manav Bansal, Arpit Chhabra, Niraj Singhal, "Smart City-Shrewd Vehicle Versatility Utilizing IOT," *International Journal of Engineering Trends and Technology,* Vol.70, No.3, Pp.29-36, 2022.

[3] H. Lipu, M. Hannan, A. Hussain, A. Ayob, M. H. Saad, and K. M. Muttaqi, "State of Charge Estimation in Lithium-Ion Batteries: A Neural Network Optimization Approach," *Electronics,* Vol.9, No.9, Pp.1546, 2020.

[4] X. Shu, G. Li, J. Shen, W. Yan, Z. Chen, and Y. Liu, "An Adaptive Fusion Estimation Algorithm for State of Charge of Lithium-Ion Batteries Considering Wide Operating Temperature and Degradation," *Journal of Power Sources,* Vol.462, No.228132, 2020.

[5] Y. Gao, C. Zhu, X. Zhang, and B. Guo, "Implementation and Evaluation of A Practical Electrochemical-Thermal Model of Lithium-Ion Batteries for EV Battery Management System," *Energy,* Vol. 221, No. 119688, 2021.

[6] X. Wang, X. Wei, J. Zhu, H. Dai, Y. Zheng, X. Xu, and Q. Chen, "A Review of Modeling, Acquisition, and Application of Lithium-Ion Battery Impedance for Onboard Battery Management," *Etransportation,* Vol.7, No.100093, 2021.

[7] H. Dai, B. Jiang, X. Hu, X. Lin, X. Wei, and M. Pecht, "Advanced Battery Management Strategies for A Sustainable Energy Future: Multilayer Design Concepts and Research Trends," *Renewable and Sustainable Energy Reviews,* Vol.138, No.110480, 2021.

[8] H. A. Gabbar, A. M. Othman, and M. R. Abdussami, "Review of Battery Management Systems (BMS) Development and Industrial Standards Technologies," Vol.9, No.2, Pp.28, 2021.

[9] N. G. Panwar, S. Singh, A. Garg, A. K. Gupta, and L. Gao, “Recent Advancements in Battery Management System for Li-Ion Batteries of Electric Vehicles: Future Role of Digital Twin, Cyber-Physical Systems, Battery Swapping Technology and Non-Destructive Testing,” *Energy Technology*, 2021.

[10] N. Mohammed and A. M. Saif, “Programmable Logic Controller-Based Lithium-Ion Battery Management System for Accurate State of Charge Estimation,” *Computers & Electrical Engineering*, Vol.93, No.107306, 2021.

[11] C. A., J. B. Holm-Nielsen, P. Sanjeevikumar, and S. Himavathi,”Artificial Intelligent Techniques for Electric and Hybrid Electric Vehicles,” *Wiley-Scrivener*, 2020.

[12] C. Liu, Q. Li, and K. Wang, “State-of-Charge Estimation and Remaining Useful Life Prediction of Supercapacitors,” *Renewable and Sustainable Energy Reviews*, Vol.150, No.111408, 2021.

[13] H. F. Khan, A. Hanif, M. U. Ali, and A. Zafar, “A Lagrange Multiplier and Sigma Point Kalman Filter Based Fused Methodology for Online State of Charge Estimation of Lithium-Ion Batteries,” *Journal of Energy Storage*, Vol. 41, No.102843, 2021.

[14] C. Jiang, S. Wang, B. Wu, C. Fernandez, X. Xiong, and J. Coffie-Ken, “A State- of-Charge Estimation Method of the Power Lithium-Ion Battery in Complex Conditions Based on Adaptive Square Root Extended Kalman Filter,” *Energy*, Vol.219, No.119603, 2021.

[15] V. Chandran, C. K Patil, A. Karthick, D. Ganeshaperumal, R. Rahim, and A. Ghosh, “State of Charge Estimation of Lithium-Ion Battery for Electric Vehicles Using Machine Learning Algorithms,” *World Electric Vehicle Journal*, Vol.12, No.1, Pp.38, 2021.

[16] J. Tian, R. Xiong, W. Shen, and J. Lu, “State-of-Charge Estimation of Lifepo4 Batteries in Electric Vehicles: A Deep-Learning Enabled Approach,” *Applied Energy*, Vol. 291, No.116812, 2021.

[17] P. Xu, B. Liu, X. Hu, T. Ouyang, and N. Chen, “State-of-Charge Estimation for Lithium-Ion Batteries Based on Fuzzy Information Granulation and Asymmetric Gaussian Membership Function,” *IEEE Transactions on Industrial Electronics*, 2021.

[18] Poushali Pal, Devabalaji K. R, S. Priyadarshini "Design of Battery management system for Residential applications" International Journal of Engineering Trends and Technology 68.3(2020):12-17.

[19] M. H. Lipu, M. Hannan, T. F. Karim, A. Hussain, M. H. Saad, A. Ayob, M. S. Miah, and T. Mahlia, “Intelligent Algorithms and Control Strategies for Battery Management System in Electric Vehicles: Progress, Challenges and Future Outlook,” *Journal of Cleaner Production*, 2021.

[20] F. Xiao, C. Li, Y. Fan, G. Yang, and X. Tang, “State of Charge Estimation for Lithium-Ion Battery Based on Gaussian Process Regression with Deep Recurrent Kernel,” *International Journal of Electrical Power & Energy Systems*, Vol.124, No. 106369, 2021.

[21] P. Xu, J. Li, C. Sun, G. Yang, and F. Sun, “Adaptive State-of-Charge Estimation for Lithium-Ion Batteries By Considering Capacity Degradation,” *Electronics*, Vol.10, No.2, Pp.122, 2021.

[22] C. Bian, H. He, S. Yang, and T. Huang, “State-of-Charge Sequence Estimation of Lithium-Ion Battery Based on Bidirectional Long Short-Term Memory Encoder-Decoder Architecture,” *Journal of Power Sources*, Vol.449, No.227558, 2020.

[23] Euclidean Distance Formula - Derivation, Examples. Https://Www.Cuemath.Com/Euclidean-Distance-Formula/.

[24] X. Gu, K. See, Y. Wang, L. Zhao, and W. Pu, “The Sliding Window and SHAP Theory—An Improved System with A Long Short-Term Memory Network Model for State of Charge Prediction in Electric Vehicle Application,” *Energies*, Vol.14, No.12, Pp. 3692, 2021.

[25] X. Yang, S. Wang, W. Xu, J. Qiao, C. Yu, and C. Fernandez, “Fuzzy Adaptive Singular Value Decomposition Cubature Kalman Filtering Algorithm for Lithium-Ion Battery State-of-Charge Estimation,” *International Journal of Circuit Theory and Applications*, 2021.

[26] W.-Y. Chang, ”Estimation of the State of Charge for An LFP Battery Using A Hybrid Method That Combines A RBF Neural Network, An OLS Algorithm and AGA,” *International Journal of Electrical Power and Energy Systems*, Vol.53, Pp.603–611, 2013.

[27] D. Sun, X. Yu, C. Wang, C. Zhang, R. Huang, Q. Zhou, T. Amietszajew, and R. Bhagat, “State of Charge Estimation for Lithium-Ion Battery Based on An Intelligent Adaptive Extended Kalman Filter with Improved Noise Estimator," *Energy*, Vol.214, No. 119025, 2021.

[28] Y. Guo, Z. Yang, K. Liu, Y. Zhang, and W. Feng, “A Compact and Optimized Neural Network Approach for Battery State-of-Charge Estimation of Energy Storage System," *Energy*, Vol.219, No.119529, 2021.

[29] M. Wei, M. Ye, J. B. Li, Q. Wang, and X. X. Xu, “State of Charge Estimation for Lithium-Ion Batteries Using Dynamic Neural Network Based on Sine Cosine Algorithm,” *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*: 09544070211018038, 2021.

[30] D. Cui, B. Xia, R. Zhang, Z. Sun, Z. Lao, W. Wang, W. Sun, Y. Lai, and M. Wang, “A Novel Intelligent Method for the State of Charge Estimation of Lithium-Ion Batteries Using A Discrete Wavelet Transform-Based Wavelet Neural Network,” *Energies*, Vol.11, No.4, Pp. 995, 2018.

[31] D. Johnson, “Back Propagation Neural Network: What Is Backpropagation Algorithm in Machine Learning?” in: Https://Www.Guru99.Com/Backpropogation-Neural-Network.Html

[32] Mazur, “A Step-By-Step Backpropagation Example.” in: Https://Mattmazur.Com/2015/03/17/A-Step-By-Step-Backpropagation-Example/

[33] M. S. H. Lipu, M. A. Hannan, A. Hussain, M. H. Saad, A. Ayob, and M. N. Uddin, "Extreme Learning Machine Model for State-of-Charge Estimation of Lithium-Ion Battery Using Gravitational Search Algorithm," *IEEE Transactions on Industry Applications* Vol.55, No.4, Pp. 4225–4234, 2019.
[34] G. Zhang, B. Xia, and J. Wang, "Intelligent State of Charge Estimation of Lithium-Ion Batteries Based on LM Optimized Backpropagation Neural Network," *Journal of Energy Storage*, Vol.44, No.103442, 2021.
[35] "Linear Regression." in: Https://En.Wikipedia.Org/Wiki/Linear_Regression.
[36] "Implementation of K Nearest Neighbors." in: Https://Www.Geeksforgeeks.Org/Implementation-K-Nearest-Neighbors/
[37] "K-Nearest Neighbors (KNN) with Python." in: Https://Datascienceplus.Com/K-Nearest-Neighbors-Knn-with-Python/
[38] "What Are the Advantages and Disadvantages of Regression Algorithms[Online]." in: Https://Www.I2tutorials.Com/What-Are-the-Advantages-and-Disadvantages-of- Regression-Algorithms/2019
[39] "Advantages and Disadvantages of Time Series." in: Https://Rb.Gy/Aoxmml. 2020.
[40] "What are the Advantages and Disadvantages of KNN Classifier?" in: Https://Www.I2tutorials.Com/Advantages-and-Disadvantages-of-Knn-Classifier/2019.
[41] H. Yu, T. Xie, S. Paszczynski, and B. M. Wilamowski, "Advantages of Radial Basis Function Networks for Dynamic System Design," *IEEE Transactions on Industrial Electronics*, Vol.58, No.12, Pp. 5438–5450, 2011. DOI: 10.1109/TIE.2011.2164773.
[42] D. Johnson, "Back Propagation Neural Network: What Is Backpropagation Algorithm in Machine Learning? [Online]". in: Https://Www.Guru99.Com/Backpropagation-Neuralnetwork.Html. 2021.
[43] Y. Chen, C. Li, S. Chen, H. Ren, and Z. Gao, "A Combined Robust Approach Based on Auto-Regressive Long Short-Term Memory Network and Moving Horizon Estimation for State-of-Charge Estimation of Lithium-Ion Batteries," *International Journal of Energy Research*, 2021.