Survey on Estimation Methods for EV Battery Health using ML Techniques

Arya Jha, K Rahul Annamalai, C R Amrutha Varshini, Ayush Tiwari, K. Deepa, V. Sailaja

Department of Electrical and Electronics Engineering, Amrita School of Engineering, Bengaluru, Amrita Vishwa Vidyapeetham, India, aryajha0512@gmail.com, k_deepa@blr.amrita.edu, v_sailaja@blr.amrita.edu

Abstract.

Battery management system (BMS) is one of the vital components of an electric vehicle's battery. In BMS, input parameters are extracted from the main system and data related to the same is fed to the algorithm. State of Health and the State of Charge, abbreviated as SoH and SoC, respectively, are two crucial factors from which the life, reliability, efficiency, and safety of a battery are indicated. When dealing with a large dataset, Machine Learning (ML) approaches are utilized to make these factors' predicted value relatively precise to the real value. The result ensues from the past information as well as the present information, which is called the training for the ML technique. This paper compares the various ML methods based on the parameters as accuracy, training dataset, requirement, complexity, and temperature. It suggests LSTM as the appropriate method for the estimation of SoH and SoC of the battery.

Keywords. State of Health (SoH), Long Short-Term Memory (LSTM), State of Charge (SoC), Machine Learning (ML).

1. INTRODUCTION

The solution to the growing concern regarding the environment revolves around minimizing the use of non-renewable resources and increasing the efficiency of renewable resources, making them more economical [4]. One of the sectors which affect the environment by about 23-25% is the transportation industry. To minimize this percentage, electric vehicles (EVs) were introduced, and they are a boon to this industry [2, 15]. The demand for EVs is increasing day by day, seeing the advantages of high energy, power density and long lifespan[31]. In electric vehicles, batteries are used in the place of fuels which decreases the emission of carbon dioxide. [26] As the battery is a chemical energy storage source, for efficient working of a battery, it is important to know the behaviour of battery parameters like voltage, current, and temperature[30]. Battery management system (BMS) of an EV battery has a significant role in predicting the parameters related to battery health accurately [5]. BMS's role in battery includes protecting the battery, preventing over-discharge, improving the battery parameters, allowing applications to make rational control strategies to save energy and estimating of SoC and SoH of the battery. Both the parameters enable the study of the performance of battery ageing as the battery goes through several cycles [3, 29]. Here, one process means the completion of the loop of one-time charging and discharging of the battery. In this work, large amounts of data inputs are taken under consideration for predicting SoH. Therefore, this paper emphasizes more on the analysis of different Machine

Learning (ML) methods that are used for the prediction of SoH. For the precise and accurate estimation of SoH, different machine learning methods like Feedforward neural network (FNN), Support vector machine (SVM), Backpropagation Neural Network BP(NN), Radial Basis Function (RBF- NN), Extreme Learning Machine (ELM) , Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are compared based on training speed, memory cell, efficiency, etc. The procedure of formulation for respective ML methods has been described and demonstrated with block diagrams of operation and working. Also, the comparison has been made featuring the most appropriate method to use for SoH estimation as the conclusion.

2. SYSTEM DESCRIPTION

2.1. State of Health (SoH)

SoH of an EV battery suggests the functionality of the battery at the cell or pack level. It illustrates the ratio of maximum available capacity denoted by C_P that is used to the nominal rated capacity C_N that was not used as shown in Equation (1)[1, 27]. In simple terms, the number of times the battery can be charged and discharged is specified by the SoH of the battery.

$$\text{SoH (\%)} = \frac{C_P}{C_N} \text{ x } 100 \quad (1)$$

However, SoH is an indicator that requires details of health-related parameters such as ageing, history etc. Therefore, evaluating the SoH accurately increases the battery's life and avoids performance degradation [14]. Based on the analysis and working of the system, there are different models to forecast SoH precisely. There are many model-based SoH prediction methods-model-based, data-driven methods, hybrid methods and other methods that include such as SoC etc.

2.2. ML methods for SoH estimation

Different ML methods are categorised as in Figure 1 and discussed based on memory unit use, speed, training parameter and performance[1-7].

2.2.1. FNN 2.2.2. SVM 2.2.3. BP-NN 2.2.4. RBF-NN

2.2.5. ELM 2.2.6. RNN 2.2.6.1. LSTM 2.2.6.2. GRU

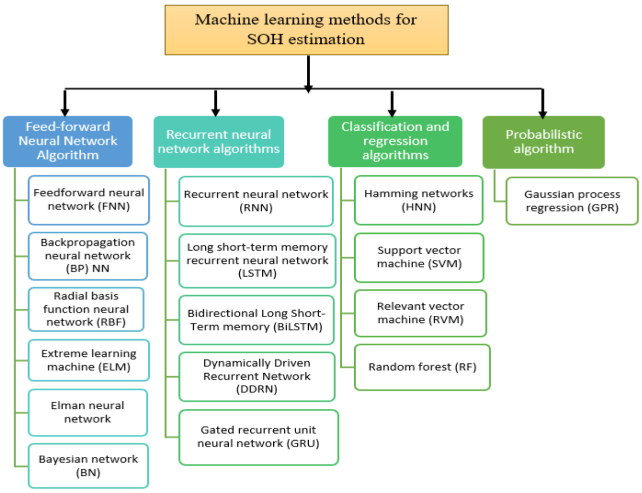

Figure 1. Machine learning methods for SOH estimation [1,4]

2.2.1. Feedforward Neural Network (FNN)

A Neural Network comprises input layers with input neurons in it, followed by several intermediate hidden layers to finally give an output [1, 12]. For this model to be understood, a k- means algorithm approach has been taken where the data has been extracted, which is based on the battery's parameters like current, voltage and temperature from 10 drive cycle so that more subregions could be detected and taken into consideration. A total of 44 datasets were created - 11 each for each of the temperatures 10 deg, 25 deg, 45 deg and 60 deg and with this, a point cloud distribution based is created. Here each sub-region is taken as input for this method, which is around 80, which means 80 inputs with 80 hidden layers of nodes giving a single output. Here the nodes are neurons that activate themselves to receive data from the previous set of information layers, and links that are used for mapping purposes are the weights.

This neural network aims to balance the weight links to achieve accuracy with minor modelling error, i.e., overfitting [7]. When this is compared with SVM models, it has been observed that the first showed commendable results than SVM models. But this model has some disadvantages like adjustment to variations from cell to cell in a pack and updating that in histogram from time to time. The calculation for FNN can be done by following (2) [28]:

$$a_n = f(\mu_n)$$

$$\mu_n = \sum p_{nm} q_m$$

$$f(\mu) = \frac{1}{1 + exp(-\mu)}$$

$$U = \frac{1}{2}(a_0 - a_{0r})^2$$

$$p_{nm}{}^{(j+1)} = p_{nm}{}^{(j)} - \beta\left(\frac{\partial F}{\partial q_{mn}}\right)^{j} \quad (2)$$

p_{nm}= weight coefficient $\quad$ a_n = output

μ_n = nth neuron potential $\quad$ f(μ) = transfer function

U = object function $\quad$ β = learning rate

a_0 and a_{0r} = output neuron's computed and required activities

2.2.2. Support Vector Machine (SVM)

Earlier, SVM was created for the problems related to classification and is further being used for solving the regression problem in a method known as Support Vector Regression, abbreviated as SVR [5]. Data which are not linearly separable, like battery environmental conditions and internal parameters, are solved by this ML technique. Steps involved in modelling SVM models are extraction, data processing, optimal SVM parameters searching, data training, data prediction, etc. The kernel function is invoked in the new feature space for the transformation of the initial input space into a high-dimensional feature space [1].

$$min_{m,c} = \frac{1}{2}\alpha^{T'}\alpha$$

$$q_n - \alpha \cdot a_n - c \leq \mu$$

$$\alpha \cdot a_n + c - q_n \leq \mu$$

$$f(a) = \sum_{n=1}^{N}(\beta_n - \beta *_n)\, K(a, a_n) + b \quad (3)$$

Following the mapping of the vector to a higher dimension, two parallel hyperplanes are determined, dividing the data on either side of the hyperplane. The formulae to be followed for the related problem are given in (3), where,

μ = toleration deviation $\quad$ α and c = found from Lagrange multipliers $\beta_n and\ \beta *_n$

f(a) = approximation function

2.2.3. Backpropagation Neural Network BP(NN)

Backpropagation NN BP(NN) is a multilayer feedforward NN in the traditional sense, which has an input layer, hidden layers (few), and an output layer [24]. In directed learning algorithms, the error back propagation algorithm is commonly used [16]. In case if accuracy is not attained between the expected and predicted value, propagation takes place and error propagates back from the output layer [1-2, 9, 25]. Under this method, threshold and weight are adjusted to get the convergence of error between expected output and network output until accuracy is met [1]. Stepwise formulation for BP(NN) in given in (4-8).

$$Bp_k = \sum_{j=0}^{n} a_{k,j}x_j + \emptyset\phi_{k,j} \quad (4)$$

n = number of neurons $\quad$ i to n = input neuron number range

$a_{k,j}$= weight of i and n range $\quad$ $\emptyset\phi_{k,j}$ = neuron threshold

$$b_k = f(Bp_k) \tag{5}$$

f(B_{pk}) = sigmoid function which is represented as an activation function.

In the below equation, $S = \alpha \times s$, where take alpha to be compression of the activation function and the other terms are considered just like the above equation.

$$f(Bp_k) = \frac{1}{1+e^{-S}} \tag{6}$$

$$Bp_m = \sum_{j=0}^{n} c_{jm} y_j + \emptyset\phi_{jm} \tag{7}$$

$$d_f = f(Bp_m) \tag{8}$$

2.2.4. Radial Basis Function (RBF) NN

For the hidden layer in RBF, the activation function is nonlinear and hence RBF can be used for any nonlinear function [27]. It provides faster convergence as compared to other methods, including Backpropagation neural network [19-21, 11]. The formulation for RBF selection has been given in (9), (10)[1].

$$e_i = \delta\,(x, y_i, z_i) = \sum_{i=1}^{n} exp\left(\frac{-||x-y_i||^2}{2{z_i}^2}\right) \tag{9}$$

$$\mathrm{E} = \left(\sum_{\mathrm{i}=1}^{\infty} \mathrm{m_i}\ \mathrm{n_i}\right) + \mathrm{B}_2 \tag{10}$$

Here, e(i) is taken as a nonlinear Gaussian function, y = average and z = standard deviation, which results in the output function given in (9), (10).

2.2.5. Extreme Learning Machine (ELM)

ELM proves to be most effective in clustering, classification, regression, and feature learning application areas [22].The features of ELM include the use of generalized theory for optimization. Moreover, the linear independence of random hidden neurons has been demonstrated by ELM, and it can be applied to almost any nonlinear piecewise continuous function. It exhibits the linear independence of random hidden neurons and expands to kernels and a higher degree of mapping of hidden instances. It also shows how, in the ELM framework, hidden node data autonomous parameters may be used to link ridge rectification, system stability, theoretically based neural network creation, maximum margin, and network optimization requirements. [8, 17]. The given set of equations (11) gives the step calculation for ELM.

$$\sum_{n=1}^{N} \boldsymbol{\delta}_n k(P_n \bullet X_i + b_n) = q_{n\,,}\ i = 1, \ldots, M$$

$$\|\ q_n - h_n\| = 0$$

$$\sum_{n=1}^{N} \boldsymbol{\delta}_n k(P_n \bullet X_i + b_n) = h_{n\,,}\ i = 1, \ldots, M$$

$$J\delta = \mathrm{H}$$

J (P_1,… P_R, b_1,… b_R, Y_1,… Y_M)

$$= \begin{bmatrix} k(p_1 \cdot x_1 + b_1) & \cdot & \cdot & \cdot & k(p_1 \cdot x_1 + b_R) \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ k(p_1 \cdot x_M + b_1) & \cdot & \cdot & \cdot & k(p_1 \cdot x_M + b_R) \end{bmatrix}_{M \times R}$$

$$\delta = J^{\dagger} H \quad (11)$$

Here, X= Input from collected sample

h = Label vector corresponding to training sample

M = Total samples N = Number of hidden nodes

k(x) = Activation function of hidden layer P = Hidden layer's input weight

δ = Output weight J= Hidden layer output matrix

2.2.6. Recurrent Neural Network (RNN)

RNN, is an appropriate ML technique for the short-term sequence as it follows a close loop for data passing where the past information is used [1, 4]. The disadvantage of this method is gradient vanishing while training the data. This is occurring because only for a certain time limit does RNN possesses past information. The actually hidden layer of RNN includes the current information with the recursion of time, resulting in information loss [6, 14]. This way, it draws a limit to the RNN structure resulting in the disadvantage of gradient vanishing. Calculation of RNN has been demonstrated in (12).

$$t_h = \gamma(W_i \times A_t + H_W \times t_{h-1} + S) \quad (12)$$

t_h = hidden layer activations in time t ( ) = activation function

A_t = input vector W_i = weight of the input vector

H_w = weight of hidden layer activations S = bias

2.2.6.1. Long Short-Term Memory (LSTM)

LSTM is one of the types of Recurrent Neural network (RNN) [3]. Moreover, the improved learning of the Long short-term memory is that it works on the shortcomings of traditional RNN, such as gradient vanishing. LSTM is considered over RNN because of the difference in the number of states. In RNN, only one state exists, whereas in LSTM, four states are present in one cycle. In this method, huge data is fed to train the models using sequences which keep track of persistent unit state and is used for decision making the task of whether to retain or store the information for further operation or to be forgotten. The computation procedure of LSTM has been given in (13).

Here n, I, O, and m denote the forget, input, output gates and memory cells, respectively[1].

b = forget gate bias $\quad$ W_o, W_i = last step output and input weight

α = activation function $\quad$ tanh = tan hyperbolic function

P_{in} and P_{on-1} = Input and output of instantaneous step

P_n= Internal variable of LSTM

$$f_n = \alpha(b_f + P_{in}W_{if} + P_{on-1}W_{of})$$

$$i_n = \alpha(b_i + P_{in}W_{ii} + P_{on-1}W_{oi})$$

$$g_n = \tanh(b_g + P_{in}W_{ig} + P_{on-1}W_{og})$$

$$m_n = m_{n-1}f_n + g_n i_n$$

$$O = \alpha(b_o + P_{in}W_{io} + P_{on-1}W_{oo})$$

$$P_{on} = \tanh(p_n) \times O \quad (13)$$

i. Explanation of battery system

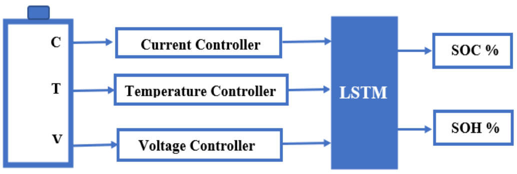

Figure 2. Battery system block diagram

For SoH estimation of the battery using the appropriate ML technique, that is, LSTM, huge data should be provided to trace the continuous change in parameter and to extract the approximately near value of actual SoH of the battery. For the more precise and accurate value of SoH, readings are taken for a longer duration which decreases the extent of the error. As shown in Figure.2, current, voltage, and temperature have been taken as the variable parameters, which have been traced against time to give the resultant SoH of the battery following feeding the input data of I, V, T to LSTM for training and data interpretation.

ii. Working of LSTM

LSTM layer has been shown in Figure.3 [2], where the input data layer at instantaneous step time n and hidden layer at n-1 step time are denoted as $\alpha_{\mathbf{n}}$ and h_{n-1}, respectively; Input, output, forget gates and memory cells are given by i_t, O_t, f_n, and $M_{k,}$ respectively. It suggests that in a closed-loop, information is passed in a neural network in a recurrent pattern where the output or intermediate state can be used as an input[13]. As LSTM involves long sequential data and uses past information, it makes SoH estimation easy [9, 18]. It stores the data and transfers the past or previous and current state data, which is used in the future state and acts as feedback [3] friendly algorithm using memory cell m_n.

The forget gate f_n decides on the information and how much of it will be useful and needed from m_{n-1} and should be passed to the next step. The input gate decides on the amount of information that should be passed to the memory cell, and the output gate O_n is responsible for the amount of information available that should be computed in the memory cell and will be counted in the output denoted by h_n.

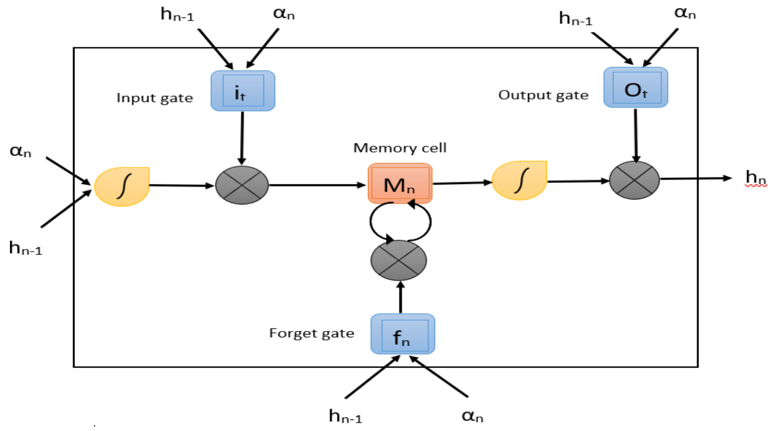

Figure 3. Block diagram for LSTM working

Working of LSTM has been illustrated in Figure.3[2] as well as Workflow of estimation of SoH involving the step of feeding input (Voltage, Current, Temperature), LSTM operation, and output extraction has been shown in Figure.4 [2].

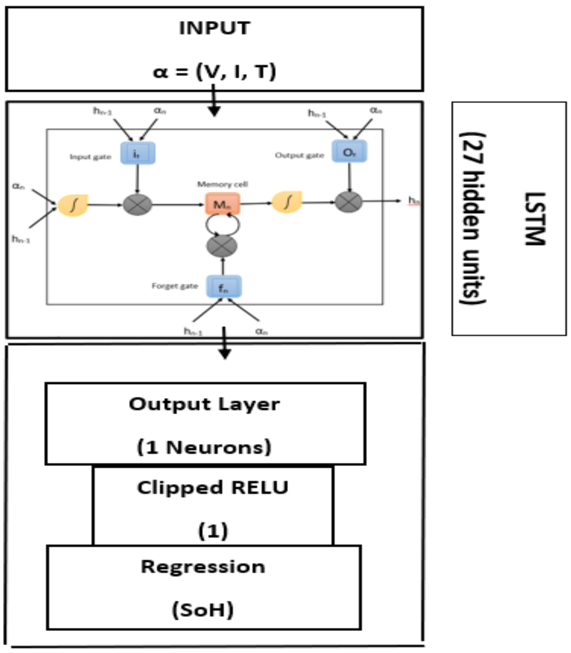

Figure 4. Estimation structure of LSTM for SoH

2.2.6.2. Gated Recurrent Unit

Based on gate control, RNN has been extended to a Gated recurrent unit (GRU), where it shares most of the features of LSTM NN [13, 23]. Integration happens to the input and forgetting gates of LSTM into an update gate. The structure of GRU is simpler as compared to LSTM. Moreover, training speed and prediction efficiency are higher. The two gates, the update gate and reset gate, determine the amount of previous information that should be passed and the amount of information that should be neglected or eliminated, respectively. Taking vast amounts of data under consideration for the inputs Voltage (V), Current (I) and Temperature (T), GRU does not give accuracy as much as LSTM NN [4]. Following are the equations involved in the computation of GRU (14) [18]:

$$a_t = \alpha(y_t W^a + H^a n_{t-1} + s_z)$$

$$q_t = \alpha\left(y_t W^q + H^q n_{t-1} + s_q\right)$$

$$n'_t = \tanh(q_t \times n_{t-1} H + y_t W + s)$$
$$n_t = a_t \times n_{t-1} + (1 - a_t) \times n'_t \tag{14}$$

W^a, W^q, W = corresponding input vector weight matrices

H^a, H^q, H = previous time step weight matrices

s_q, s_a, s = biases

α = logistics sigmoid function

q_t = reset gate

a_t = update gate

n'_t = candidate hidden layer

3. COMPARISON OF ML METHODS

In Table 1, various ML methods have been listed and compared. Given the advantages and disadvantages, which demonstrate that LSTM and GRU are appropriate methods for the estimation of the precise and accurate value of SoH. All the methods listed are used for nonlinear data analysis, but BP-NN and RBF-NN lack efficiency, whereas, in ELM and RNN, problems of data training and gradient vanishing are encountered, respectively.

Methods	Features/ Advantages	Disadvantages
BP-NN **[1]**	● Multilayer feedforward NN ● Comprises of - the input layer, an output layer followed by a few hidden layers ● Backpropagation of error and correction weight ● Until the error is reduced to the accepted limit signal, forward propagation and error backpropagation takes place	● Complexity due to net layers as the number is not fixed for the initial step ● Working efficiency is less
RBF-NN **[1]**	● Faster convergence ● Nonlinear activation function for hidden layer (usually) ● Good performance	● Less operating efficiency ● Easily falls into local optimality
ELM **[1, 18]**	● Faster training speed while ensuring the estimation accuracy ● Time of parameter optimization is reduced ● Better prediction accuracy, faster calculation speed	● Batch-based algorithm ● During the training phase, all the training data is needed to implement training and testing rather than updating the arrival of new data.
Elman-NN	● Embedded one-step delay mechanism ● Global stability, time-varying ability ● Dynamic modelling ● Fast approaching speed	● Easily falls into local optimality ● Slow training operation
RNN **[1, 4, 7, 10]**	● The impact of temperature is taken into consideration ● Sequence data processing with varying length ● Presence of parameter sharing ● Does not operate on fixed-length input ● Recurrent connection possible ● Self-feedback present	● No spatial relationship ● The range of context information is limited ● The problem of gradient vanishing. ● Battery ageing happens under high temperatures ● Implementation of constant charging/discharging for creating the dataset

LSTM **[1-6, 10]**	● Consists of a memory cell multilayer framework ● Effect of temperature is taken under consideration ● Maintains a persistent unit state as well as allows one to choose which information should be preserved and which should be forgotten. ● Gives support to the real-world driving platform because of the practical EV environment. ● Tracks for a longer time with accuracy	● Complexity in training execution ● Difficulty in the acceleration of training ● I/V pattern is needed for the account of battery degradation (the difference is there depending upon the battery chemistry)
GURU **[1]**	● Based on the gate control ● Input and Forgetting gates (of LSTM) get integrated into an update gate ● Simpler structure than LSTM ● When compared to LSTM, its training and prediction efficiency is higher ● Has fewer parameters	● Possibility of the uncertainty of battery deterioration and overfitting ● Accuracy is less as compared to LSTM for a greater number of data ● Sensitive to a Kernel function ● Higher computational cost compared to LSTM

Table 1. ML method comparison

4. CONCLUSION

In this paper, different ML techniques have been discussed with advantages and disadvantages. The performance and accurate estimation of SoH have been analyzed by comparing the methods. The main focus of this paper is the accurate estimation of SoH, which has been seen in the LSTM method. In LSTM, a huge amount of data has been trained, which dominates the advantages of GRU. Although GRU is easy to modify, faster to train and does not need memory units, or fewer training parameters, LSTM is more accurate compared to GRU when a longer sequence is used and is more accurate too. LSTM also rectifies the problem of gradient vanishing.

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Biographies

Arya Jha is pursuing the bachelor's degree in Electrical and Electronics Engineering from Amrita School of Engineering, Bengaluru, member of IEEE student branch, EXICOM member of IEEE PES and IAS joint student branch chapter Bangalore section and pursued a certification course on Data Science with applied python as well as headed Bangalore section ambassadors for PES Day 2022 and served as CSAC Ambassador for Online course category. Her area of interest involves e-mobility, Data Science, and Renewable energy technologies.

K Rahul Annamalai is pursuing the bachelor's degree in Electrical and Electronics Engineering from Amrita School of Engineering, Bengaluru and member of IEEE student branch and an EXICOM of IEEE PES and IAS and pursued a certification course on python basics, His area of interests are e-mobility, Automobile, Renewable energy technologies and power electronics.

C R Amrutha Varshini is pursuing the bachelor's degree in Electrical and Electronics Engineering from Amrita School of Engineering, Bengaluru, member of IEEE student branch, EXICOM member of IEEE sensors, IEEE PES and IAS and pursued a certification course on Data Science with applied python. Her area of interests are Electric Vehicles(BMS), Embedded Systems and Data Science.

Ayush Tiwari is pursuing the bachelor's degree in Electrical and Electronics Engineering from Amrita School of Engineering, Bengaluru and pursued a certification course on Data Science with applied python. His area of interests are Electric Vehicles(EV),Power Electronics and Renewable Energy Technologies.

Dr. K. Deepa graduated from Alagappa Chettiar college of engineering and Technology, T.N, India in 1998. She obtained M.Tech degree from Anna University, Guindy campus, T.N, India in 2005. She received Doctoral degree from Jawaharlal Nehru Technological University, Anantapur, A.P, India in 2017. Currently she is working as Associate professor in Electrical and Electronics Engineering Department, Amrita School of Engineering, Amrita Vishwa Vidyapeetham University, Bangalore, Karnataka, India. She has 23+ years of teaching experience. She is a life Member of IETE and ISTE, India and a senior member of IEEE. She has authored two textbooks on “Electrical Machines” and “Control Systems”. She has published 35+ international journal paper, 60+ papers in international conference and 6 papers in national conference. 20+ M.Tech Degrees were awarded under her guidance. She is the advisor for the IEEE-PES & IAS student branch joint chapter and advisor for IEEE WIE in Amrita School of Engineering, Bengaluru from 2015. She is also Secretary for 2021 and 2022 IEEE PELS Bangalore chapter. She ahs received the outstanding Exofficio- 2021 award for her incredible volunteering in IEEE PELS Bangalore section. Her areas of interests include Power electronics, Renewable energy technologies and Control Engineering.

V.Sailaja received the bachelor's degree in Electrical and Electronics Engineering from JNTU college of Engineering, Hyderabad in 2001, the master's degree in Power Electronis and Industrial drives from JNTU college of Engineering, Hyderabad in 2007 and currently pursuing philosophy of doctorate degree from Visvesvaraya Technological University. V.Sailaja is Assistant professor, Department of Electrical and Electronics, Amrita School of Engineering, Bangalore. Her area of interest are power quality, power electronic applications in electrical drives, battery management systems , smart grid , hybrid power systems.