Machine Learning Applied to Estimate the Battery SoH by using Various Algorithms in Python

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Abstract: Accurate state of health (SOH) prediction is significant to guarantee operation safety and avoid latent failures of lithium-ion batteries. With the development of communication and artificial intelligence technologies, a body of researches have been performed toward precise and reliable SOH prediction method based on machine learning (ML) techniques. In this the conception of SOH is defined, and the state-of the-art prediction methods are classified based on their primary implementation procedure. As an essential step in ML-based SOH algorithms, the health feature extraction methods reported in the literature are comprehensively surveyed. Next, an exhausted comparison is conducted to elaborate the development of ML-based SOH prediction techniques. Not only their advantages and disadvantages of the application in SOH prediction are reviewed but also their accuracy and execution process are fully discussed.

Finally, pivotal challenges and corresponding research directions are provided for more reliable and high-fidelity SOH prediction. The growing interest and recent breakthroughs in artificial intelligence and machine learning (ML) have actively contributed to an increase in research and development of new methods to estimate the state of health of battery by using various algorithms. This paper provides a survey of battery state estimation methods based on ML algorithms accuracy such as, Logistic Regression (LR), Linear Discriminant Analysis (LDA), Neighbors Classifier (KNN), Decision Tree Classifier (CART), and Gaussians (NB) with help of Python. Programming in Python with the help of SKlearn & Pandas.

Index Terms - Python, Machine Learning, Artificial Intelligence, Algorithm, Battery, SOH.

I. INTRODUCTION

The transportation industry faces many challenges to improve efficiency, expand performance, advance connectivity, increase autonomy, and reduce emissions. The electrified powertrain is one of the most effective technologies to enable the improvement of vehicle efficiency, but finding the way for trade-off between efficiency and costs remains a great challenge. As the battery remains one of the most expensive parts of the xEV [1], properly estimating the battery states are difficult to reducing design and development cost and increasing the overall vehicle efficiency and performance. Due to this design strategy on the battery management system (BMS) software design to perform a state of charge (SOC) and state of health (SOH) estimation accurately. The SOH methods for capacity estimation are based on amp-hour (Ah) calculation in precise reference SOC points. SOH methods for resistance estimation are more varied and range from simple averaging of delta voltage divided by delta current to recursive algorithms such as recursive least squares or advanced Kalman filter (KF) algorithms [4]. In the case of SOC estimation, one of the simplest methods is based on open circuit voltage (OCV) and coulomb counting. The other methods are referred for estimating sensor errors and uncertain model knowledge [2], [3]. Many approaches employ an equivalent circuit model (ECM) combined with KF variants for SOC estimation [4], [5]. To make these happen significant battery testing is needed to model and parameterize the algorithms. For a comprehensive review of the different approaches to the estimation of SOC, SOH, SOP, and other battery states, beyond the machine learning approaches, which are the focus of this paper, readers are referred to [2], [4], [5]. Machine learning approaches to battery state estimation have been driven by recent advances in artificial intelligence (AI) [6] in fields such as computer vision and autonomous vehicles. The Venn diagram in Fig. 1 shows how the field of AI is subdivided, including Machine Learning and its subsequent change of learning and deep learning [7]. As battery technology grows and matures, a significant amount of data is being collected and analyzed in a partially or fully automated fashion [8] to improve battery design and usage. This plethora of data has made it possible to improve BMS performance [9] via big data, the internet of things (IoT), cloud computing, and the ML methods investigated here. In the case of SOC and SOH estimation based on ML methods, the main computational load demanded by these approaches happens during its off-line training phase [10], making it feasible for implementation on typical BMS hardware.

BATTERY STATE OF HEALTH ESTIMATION

Battery SOH is a measurement of battery deterioration in comparison to a new battery. There are several ways to estimate and quantify the SOH of an xEV battery; many of the recent studies have considered either the loss of capacity (SOHc) or increase of internal resistance (SOHr). The conventional machine learning methods presented in this section for SOH estimation are grouped as the following types.

A. Feedforward neural network (FNN)
B. Recurrent neural network (RNN)
C. Radial basis function (RBF) neural network
D. Hamming networks (HNN)
E. Support Vector Machine (SVM)

A. FEEDFORWARD NEURAL NETWORK

An FNN performs non-linear mappings with an arbitrary number of inputs and outputs. For SOHc estimation, the battery capacity fading metric is typically represented by SOH = Ct C0 × 100(%) (5) where Ct is the capacity estimate at time t and Co is the new battery's nominal capacity. Battery capacity is typically measured via a particular test that spans the entire SOC range using high accuracy current measurements. However, this is achieved and usage of an xEV, so online estimation algorithms need to be employed.,

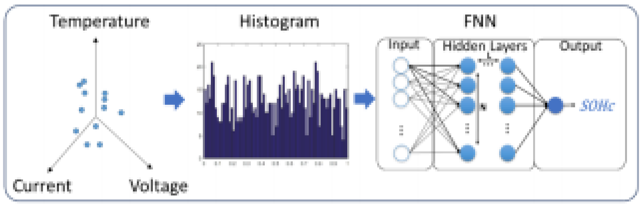


Fig. 1: Point cloud distribution based SOH FNN

B. RECURRENT NEURAL NETWORK

SOH estimation involves tracking a slow battery ageing process from battery signals that exhibit dynamic states and memory. As a result, employing a recurrent neural network that contains internal memory is a natural approach to tackle SOH estimation. A simple approach was presented in, where the authors built a dynamically driven recurrent network to estimate both the SOC and SOH of two Li-ion batteries. The SOHc estimate is fed back as delayed recurrent inputs; this gives the DDRN an associative memory feature, which is responsible for reducing the amount of data necessary to encode the dynamics in the network parameters. Other inputs to the RNN, include voltage, current, temperature, and time-delayed voltage and current. Fig. 2 shows the DDRN structure for SOH estimation. The battery life in this work was measured for several cycles versus terminal voltage

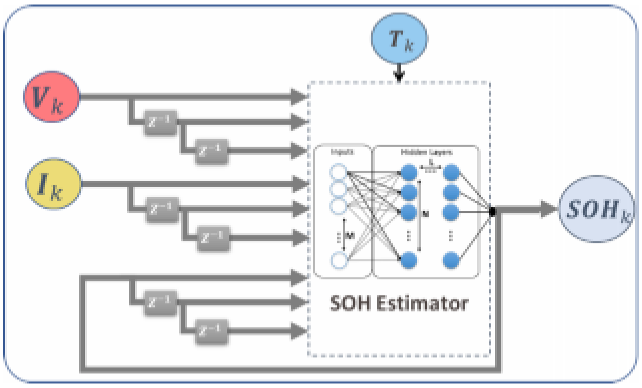


Fig.2: SOH estimator

The proposed method utilizes LSTM layers similar to those shown. The output of this LSTM block, shown in Fig.3 is a set of vectors whose elements correspond to rolling time windows at different points in time, e.g. the first corresponds to the first window segment, and the last is shifted to reach up to the most recent point in time.

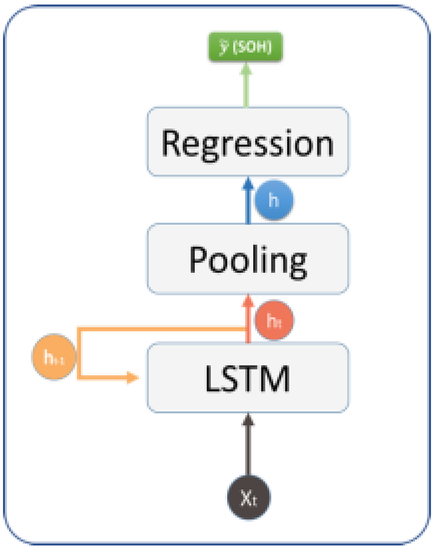


Fig.3: SOHc estimation based on the snapshot

These datasets were finally used to train RNNs capable of estimating the battery capacity and equivalent resistance and combined to estimate SOH, as shown in Fig. 4.

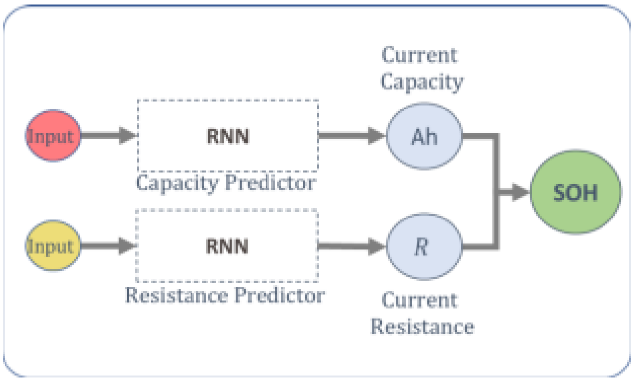


Fig.4: SOH estimation by battery capacity and resistance estimation using RNN.

The RNNs were trained and tested by using cell temperature, current, SOC variation, and the capacity and resistance of previous time steps. The SOH estimator model has shown an accurate prediction of the battery SOH when compared to the experimental data, obtaining less than 1% mean squared error (MSE) on both capacity and resistance estimations.

C. RADIAL BASIS FUNCTIONS

A sparse bayesian predictive modelling (SBPM) algorithm can be used to identify the nonlinear relation of different features within a dataset. In fig 5, the authors used an SBPM to determine the relationship between the battery capacity and voltage sequence sample entropy, where the SBPM employs the concept of radial basis functions in its design. In this case, the sample entropy is used to identify the pattern of the battery terminal voltage over time. The proposed SBPM-based method procedure is shown in Fig. 5.

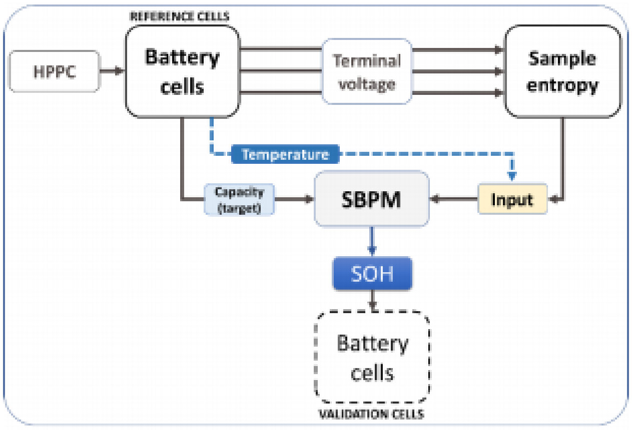


Fig.5: SBPM to estimate the SOHc.

D. HAMMING NEURAL NETWORK

A Hamming neural network (HNN) contains both an FNN and an RNN, and an example is shown in Fig. 6

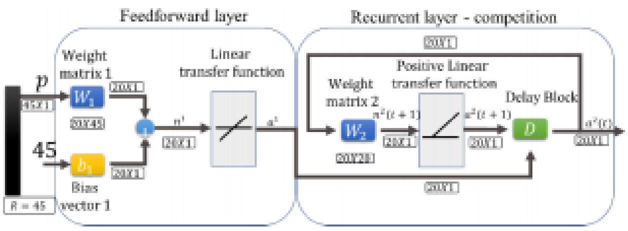


Fig.6: HNN

The HNN has found extensive applications in pattern recognition, specifically binary pattern recognition. In a Hamming Network was used in cooperation with a Dual Extended Kalman Filter (DEKF) to estimate SOC, capacity (SOHc) and resistance (SOHr). An equivalent circuit modelling approach was employed in the paper. The HNN was used to estimate the ECM parameters based on charge/discharge voltage patterns, capacity patterns, and how they change over time.

E. SUPPORT VECTOR MACHINE

The SVM was initially trained to estimate the battery voltage drop response during 10s discharge pulses to calculate the battery resistance variation (SOHr) and capacity variation (SOHc) during C/3 partial or full discharge profiles. The inputs for the SVM were the battery current, temperature and SOC.

II. COMPARISON OF SOH METHODS

Several characteristics of some of the techniques and research works presented in this section are summarized in Table 1, including the error for the SOHc, SOHr, or other SOH methods investigated, the battery type, and the temperatures considered.

Almost all of the proposed methods are able to estimate capacity or resistance with 1% or less error, showing they are all promising candidates for SOH estimation.

Table 1: Comparison of SOH methods

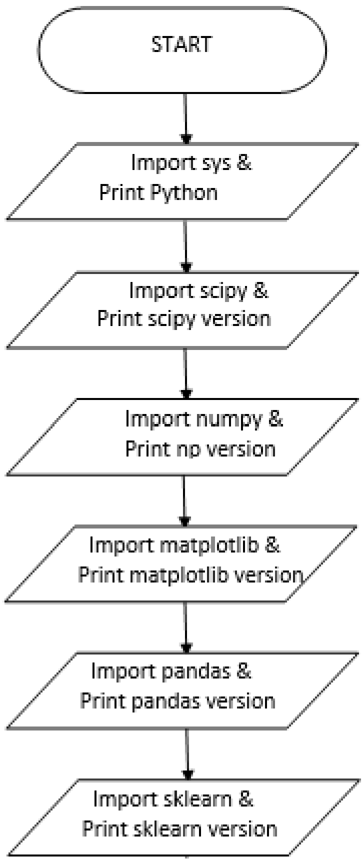
ML Method	Lowest Error (only at 25^{0}C)	SOH approach	Battery	Multi-Temperature consideration.
FNN w/ k-means[51]	SOHc: 0.66%(RMSE)	Based on capacity loss during charging	Li-ion 18650 3.1Ah	0°C, 10°C, 25°C, 45°C, and 60°C
RNN(LSTM)[56]	SOHc: 0.96%(RMSE) @ Validation R1 dataset	Based on capacity loss during charging	Li-ion 18650 3.1Ah	0°C, 10°C, 25°C, 45°C, and 60°C
DDRN[50]	SOHc: 0.1126Ah (RMSE) LFP@EOL SOHc: 0.34Ah (RMSE) LTO@EOL	Based capacity loss and number cycles	LFP (3.6V) LTO(2.6V)	25°C and 60°C (for accel. ageing)
FNN[55]	SOHr: 0.81% (MAE) LFP	Based on the internal resistance extracted from voltage variation	Li-ion IFP1865140	25°C
RNN[61]	SOHc: 0.46% (MSE) SOHr: 0.29%(MSE)	Based on Capacity and resistance estimation	NMC Li-ion (100Ah, Pouch))	40°C, and 50°C
SBPM[62]	SOHc: 1.38% (average relative capacity error)	Based capacity loss and sample entropy	NMC Li-ion Panasonic UR14650P (3.7V, 0.94Ah)	10°C, 22°C, and 35°C
FNN (SNN) w/ ECM[52]	0.32% (mean voltage deviation)@13,000km 0.28% % (mean voltage deviation)@80,000km	Based on ECM internal resistance estimation	Li-ion Saft VL6P (3.6V, 6.5 Ah)	23°C up to 50°C were considered
HNN w/ DEKF[64]	-	Based on ECM internal resistance estimation	Li-ion Samsung 18650(1.3 Ah)	No
SVM[66]	SOHc: 0.63%(RMSE) SOHr: 6.2% (RMSE)	Based on capacity and resistance variation	Li-ion Enerdel (17.5Ah, 2.5V, Pouch)	0°C to 40°C
DBN[70]	SOHr: <5%(MAE)	Based on resistance	Li-Mn (3.7V, 6Ah)	25°C and 55°C
BN[71]	SOHr: 0.28% (Avg Error) SOHr: 1.15% (Std Dev.)	Based on resistance	Li-Co (3.7V, 2.4Ah)	1°C and 23°C

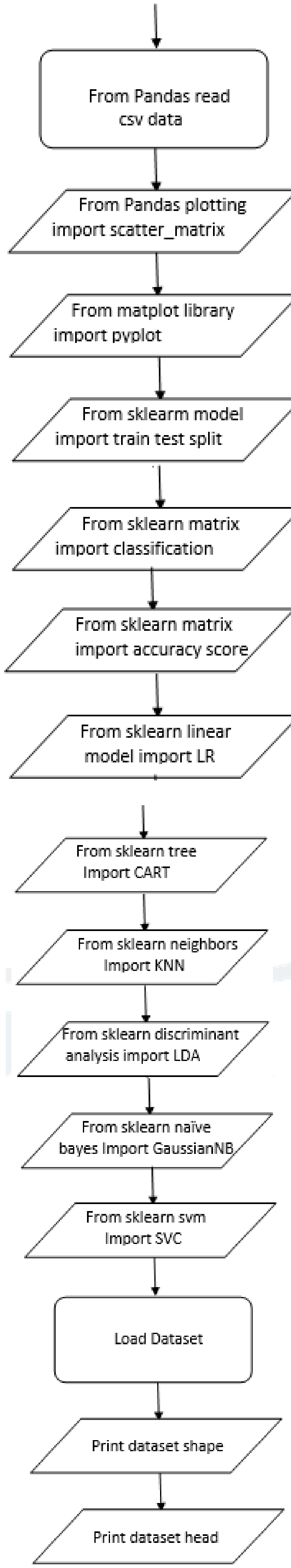
In this experiment for SOH prediction done with help of Machine Learning by using various algorithms

a. Logistic Regression (LR)
b. Decision Tree Classifier (CART)
c. KNeighbors Classifier (KNN)
d. Linear Discriminant Analysis (LDA)
e. Naïve Bayes (NB)
f. Support Vector Machine (SVM).

With help of Python, Panda & SK Learn programming, we imported the desired algorithms.

III. Flow Chart




From Pandas read
csv data
From Pandas plotting
import scatter_matrix
From matplot library
import pyplot
From sklearm model
import train test split
From sklearn matrix
import classification
From sklearn matrix
import accuracy score
From sklearn linear
model import LR
From sklearn tree
Import CART
From sklearn neighbors
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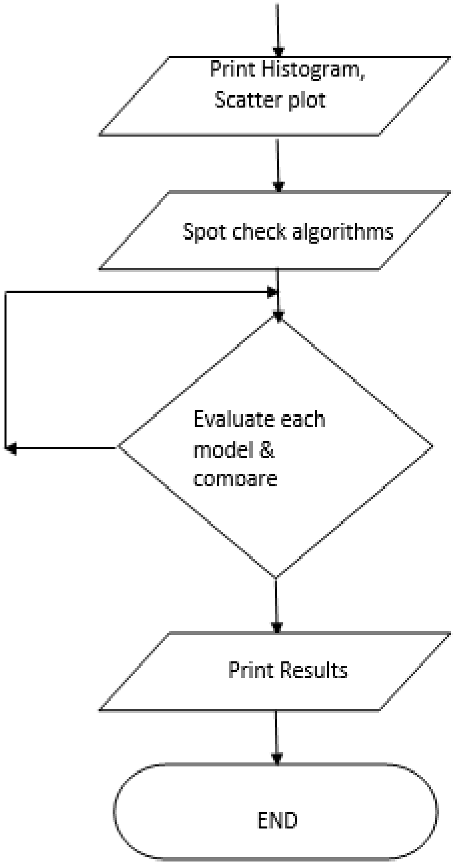
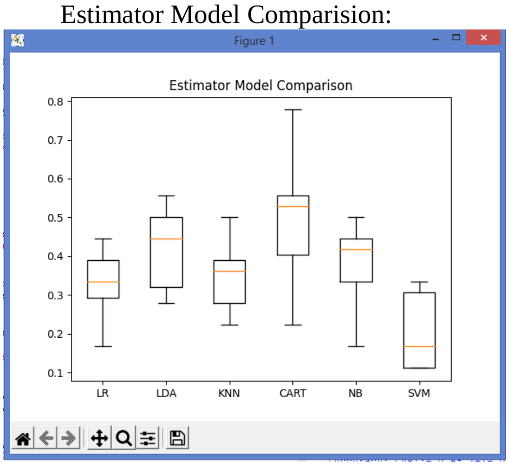
analysis import LDA
From sklearn naïve
bayes Import GaussianNB
From sklearn svm
Import SVC
Load Dataset
Print dataset shape
Print dataset head

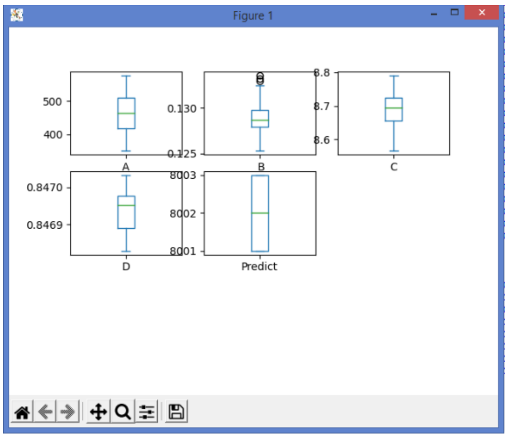


IV. Result Graphs

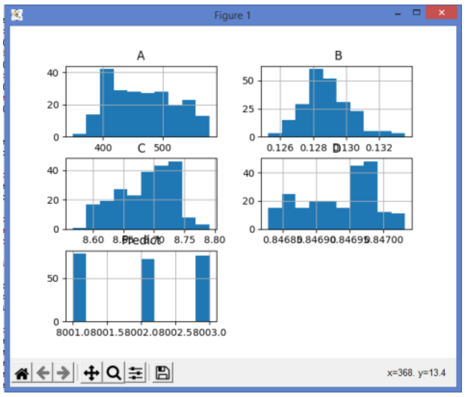
Estimator Model Comparision:



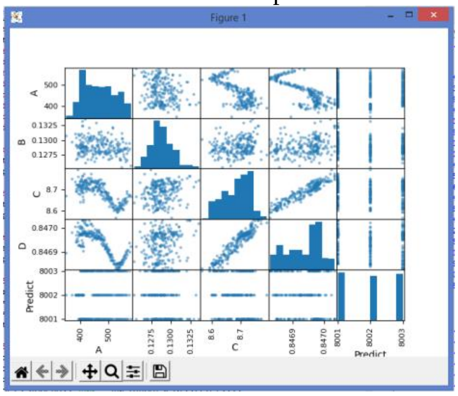
Data Distribution:



Histrogram Data Distribution:



Scatter Graph:



V. Results:

Accuracy: LR:- 0.33 (+/- 0.07)
Accuracy: LDA:- 0.43 (+/- 0.11)
Accuracy: KNN:- 0.34 (+/- 0.08)
Accuracy: CART:- 0.47 (+/- 0.13)
Accuracy: NB:- 0.38 (+/- 0.10)
Accuracy: SVM:- 0.20 (+/- 0.10)

VI. CONCLUSIONS

Based on the studies presented and summarized in this work, a wide range of machine learning approaches are suitable for the estimation of battery SOH. The data collection process can require months or years of testing, especially when SOH estimation is the objective. Despite the increasing amount of data being generated and the recent advances in the ML, their use and efficiency are still limited by not only the quantity but also the quality of the data. The computational complexity required to train and deploy ML-based models should be further investigated and compared in future work since it hasn't been addressed consistently within the surveyed work. A simple set of guidelines is suggested to be followed when training and comparing ML algorithms, which considers the use of the same validation dataset, the number of ML fitted algorithm parameters and training process repetitions.

REFERENCES

1. A. M. Andwari, A. Pesiridis, S. Rajoo, R. Martinez-Botas, and V. Esfahanian, ''A review of battery electric vehicle technology and readiness levels,'' Renew. Sustain. Energy Rev., vol. 78, pp. 414–430, Oct. 2017.
2. M. A. Hannan, M. S. H. Lipu, A. Hussain, and A. Mohamed, ''A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations,'' Renew. Sustain. Energy Rev., vol. 78, pp. 834–854, Oct. 2017.
3. A. Emadi, Advanced Electric Drive Vehicles. New York, NY, USA: CRC Press, 2015.
4. R. Zhang, B. Xia, B. Li, L. Cao, Y. Lai, W. Zheng, H. Wang, and W. Wang, ''State of the art of lithium-ion battery SOC estimation for electrical vehicles,'' Energies, vol. 11, no. 7, p. 1820, 2018.
5. M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, and P. Van den Bossche, ''Critical review of state of health estimation methods of li-ion batteries for real applications,'' Renew. Sustain. Energy Rev., vol. 56, pp. 572–587, Apr. 2016.
6. S. Zuboff, The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power, 1st ed. New York, NY, USA: PublicAffairs, 2019.
7. I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.
8. C. Vidal, M. Haußmann, D. Barroso, P. M. Shamsabadi, A. Biswas, E. Chemali, R. Ahmed, and A. Emadi, ''Hybrid energy storage system state-of-charge estimation using artificial neural network for microhybrid applications,'' in Proc. IEEE Transp. Electrific. Conf. Expo (ITEC), Long Beach, CA, USA, Jun. 2018, pp. 1075–1081.
9. H. Liu, A. Gegov, and M. Cocea, Rule Based Systems for Big Data, vol. 13. Cham, Switzerland: Springer, 2016.
10. E. Chemali, P. J. Kollmeyer, M. Preindl, and A. Emadi, ''State-of-charge estimation of li-ion batteries using deep neural
a. networks: A machine learning approach,'' J. Power Sour., vol. 400, pp. 242–255, Oct. 2018.
11. https://www.mygreatlearning.com/blog/most-used-machine-learning-algorithms-in-python/
12. https://scikit-learn.org/