A Survey on Battery State of Charge and State of Health Estimation Using Machine Learning and Deep Learning Techniques

Mandeddu Sudhakar Reddy and M. Monisha

Abstract For long-lasting electric vehicles, accurate health evaluation and lifetime prediction of lithium-ion batteries are critical. Early diagnosis of poor performance allows for prompt battery system maintenance. This lowers operating expenses and lessens the risk of accidents and malfunctions. The rise of "Big Data" analytics and related statistical/computational technologies has sparked interest in data-driven battery health estimates. In this paper, we review several articles to highlight their achievability and also environmentally friendly in production with health of battery in reality. We distinguish how machine learning and deep learning algorithms helpful in estimating SOC and SOH of Li-ion battery that are utilized in durable electric vehicles. In addition, we explained the basics of battery, cells, types of battery along with its characteristics were analyzed. Moreover, we summarized the state-of-art table comprises techniques used, which state of estimation either SOH or SOC, metrics used by various machine learning and deep learning algorithms, and discussed their benefits too.

Keywords Machine learning (ML) · State of health (SOH) · Deep learning (DL) · State of charge (SOC) · Long short-term memory (LSTM)

1 Introduction

A battery is a chemical device that stores electrical energy in the form of chemicals and then turns that stored chemical energy into direct current (DC) electric energy through an electrochemical reaction. In 1800, an Italian physicist named Alessandro Volta invented the first battery. An electric current is used to move electrons from one substance to another (called electrodes) in an electrochemical reaction in a battery.

M. Sudhakar Reddy (✉) · M. Monisha
Department of ECE, VISTAS, Chennai, India
e-mail: sudhakar.mandeddu@gmail.com

M. Monisha
e-mail: monisha.se@velsuniv.ac.in

V. K. Gunjan and J. M. Zurada (eds.), *Proceedings of 3rd International Conference on Recent Trends in Machine Learning, IoT, Smart Cities and Applications*, Lecture Notes in Networks and Systems 540, https://doi.org/10.1007/978-981-19-6088-8_31

Then we are discussing about how cell and battery are collide with each other. Despite the fact that specific word series is frequently utilized, the fundamental ECU suitably energy saved space is known as a group. As previously stated, group defines essential ECU which produces electrical energy by converting chemical energy. A cell comprises of three primary components: two electrodes and electrolyte, as well as terminals, a separator, and a container in its most basic form. When it comes to electrodes, there are two sorts of electrodes: anode and cathode. The negative electrode is known as the anode that drops electrons to the peripheral path also oxidized in chemical response. The positive electrode, conversely, cathode represents electrons which are oxidized internally. This absorbs particles of electron as of everlasting circuit and is reduced in chemical response. As a result, the electrochemical oxidation–reduction reaction is responsible in power transfer series. The electrolyte is the cell's third most critical component. Between the two electrodes, an electrolyte functions as a channel for charge conversion represents as ions. As a result, electrolyte is also known as an Ionic Conductor which has ionic conductivity. A battery is typically made up of one or more "cells" that are electrically connected in series or parallel to give the required voltage and current levels depicted in Fig. 1.

The main objective of this survey is described as follows:

- To discuss about basics of batteries, cells and the working of battery as well.
- To review on several articles to make familiar about battery types along with its characteristics.
- To know how machine learning techniques helpful in estimation on battery SOC and SOH.
- To recognize how deep learning algorithms appropriate in evaluation on battery SOC and SOH.

Fig. 1 Configuration of battery

- To made comparison of several research articles related with battery to highlight the techniques utilized for battery SOH and SOC estimation.

The main contribution of this survey is to make familiar about the basic concepts of battery, cells, how battery works in electronic vehicles. Moreover, this reviewed work helpful for current researchers who are working in electronic vehicle field using modern techniques especially ML and DL algorithms. The remaining paper work is summarized as follows: Sect. 2 explains the literature survey of several existing articles regarding battery SOH and SOC estimation. Section 3 describes the types of battery along with its specific characteristics of each battery. Section 4 introduced how machine learning techniques suitable for predicting battery SOH and SOC estimation. Section 5 briefly about how deep learning algorithms useful in estimation of battery SOH and SOC. Section 6 introduces the overall survey table which described the comparison of several research works comprises of techniques used, kind of battery used, whether SOC or SOH is used, and benefits are discussed here. Section 7 explains the conclusion part of battery SOC and SOH estimation of this survey.

2 Related Work

Caliwag et al. [1] proposed hybrid method comprises of both Vector Auto Regressive Moving Average along with LSTM for predicting SOC as well as battery O_v while electric vehicle is motivated beneath CVS-40 drive cycle. This proposed approach attains least RMSE in estimation of SOC for battery in motor cycle. Erlangga et al. [2] utilized dual Kalman filter approach for Lithium battery SOC and SOH estimation. Guo et al. [3] applied the properties of battery divergence protection as well as ohmic resistance for estimating battery health (SOH) estimation. Based on accuracy metrics, the Lithium-Ion Phosphate battery health was estimated. Under varying SOH, polarization resistance does not change appreciably. The ohmic resistance is the principal cause of the battery's internal resistance variation. As a result, it is recommended to estimate the SOH of cells using ohmic resistance, which is defined as follows:

$$\mathrm{SOH} = \frac{R_{\mathrm{EOL}} - R_{\mathrm{Now}}}{R_{\mathrm{EOL}} - R_N} \times 100\%$$

When the actual capacity is 80% of the rated capacity, R_{EOL} is the value of the ohmic resistance. When the battery is made in the factory, the ohmic resistance value is R_N. In the current condition, R_{now} is the ohmic resistance value. Chang et al. [4] reviewed several articles on SOC estimating numerical approaches for all rechargeable and non-rechargeable batteries. Fan et al. [5] introduced open circuit voltage based on affine projection algorithm for estimating SOH on Li-ion battery in e-vehicles. Noura et al. [6] reviewed many articles regarding techniques of SOH estimation which are most challenging part in hybrid electric vehicles. How et al. [7] reviewed that utilization with hybrid model comprises of both data driven and model based approach for predicting SOC in Li-ion battery. Li et al. [8] reviewed on battery heath and battery lifetime in Li-ion battery using data driven approach.

3 Types of Battery Along with Its Characteristics

- Non-rechargeable batteries known as Primary,
- Rechargeable batteries are called Secondary.

The above two sorts of series are the fundamental kinds, despite the fact that there are countless different categories among kinds of series be shown in Fig. 2.

3.1 Non-rechargeable Battery

A primary battery is a simple and convenient power source as range of transferable electrical equipment like illumination, pictures, wristwatch, playthings, radios, etc. They are of the "use it and throw it away" kind because that particles are not reviving. Non-rechargeable series often low-cost, less weight, compact, and easy to use, requires little or no maintenance. The majorities of single-cell crucial series are utilized in home appliances, cylindrical and have a single cell structure (although, it is very easy to produce them in different shapes and sizes). Zinc-carbon-based batteries were used in the 1940s, during World War II, and afterward, maximum competence 50 W hour per kilogram. Major improvement in series expertise transpired among

Fig. 2 Representation of rechargeable and non-rechargeable battery

1970–1990. The famous Zn-Al Mng O_2 series invented about this time, and they gradually superseded adult Zn-C types while dominant battery.

For the current period, Zn-MO also Cd–Mr O series utilized, as a result of environmental concerns over Mercury usage, these battery types were gradually phased out.

3.2 Rechargeable Battery

The resultant series is sometimes called boosting series since this may be repeatedly charged subsequent being released. By delivering the energy during ECC in the contradictory path of their release, the substance position of the group may "recharged" to their initial position. Rechargeable batteries are utilized in two dissimilar ways.

Way 1: Rechargeable series are effectively utilized as the device which store energy somewhere they are linked to main energy source electrically as well as charged by it too and hence providing energy when needed. The major real time example is UPS named as Uninterrupted Power Supplies.

Way 2: Another group of rechargeable battery is wherever battery is utilized and release as non-rechargeable battery. On one occasion, it is fully released rather than disposed it, the battery is re-energized with proper charging device. Such kind of procedure is applicable in real time appliances such as E-vehicles, mobiles and laptops.

3.3 Characteristics of Rechargeable and Non-rechargeable Batteries

Table 1 describes the kind of battery, whether primary or secondary batteries, along with its characteristics are explained.

4 SOC and SOH Estimation

Energy Management System is utilized for retaining the secure, consistent function of battery. This comprises of cell complementary, security to guarantee the function inside secure limits of battery, estimation of battery SOC and SOH. To ensure an accurate measure of a vehicle's remaining driving range as well as optimal battery pack balancing, a reliable state of charge estimation is essential. The SOC is similar to the fuel gauge found in gasoline-powered cars. SOC refers to the amount of charge left in the battery and is calculated as the ratio of the battery's residual capacity to its

Table 1 Description of kind of battery, whether it is rechargeable, non-rechargeable and its characteristics

Kind of battery	(Rechargeable/non-rechargeable)	Characteristics
Zinc-carbon	Non-rechargeable battery	Less cost, common, availability of several sizes
Mercury	Primary cell	Life time is long, very high capacity
Magnesium	Primary cell	Life time is long, very high capacity
Lithium	Non-rechargeable battery	Greater performance, very high power compactness
Silver/zinc	Non-rechargeable battery	Greater capacity, horizontal release and valuable
Lead-Acid (LA)	Rechargeable battery	Capacity ranges from 1 to 12,000 Ah
Nickel–Cadmium (Ni–Ca)	Rechargeable battery	Life time is very long, consistent and powerful, Discharge rate is high
Nickel Metal Hydrate battery	Rechargeable battery	Very high energy density
Lithium-Ion battery	Rechargeable battery	Very high energy density, high exact energy, life time cycle is longer

nominal capacity. The state of health (SOH) estimation, which has a value ranging from 0 to 100%, is commonly used to determine battery aging. It is a monetary value that does not correspond to a physical item and is expressed as a percentage. A SOH of 100% reflects battery health at the beginning of a battery's lifetime, when capacity is at its highest, and a SOH of 0% represents battery health at the end of the battery's lifetime, when capacity is at its lowest. The difference between a fully charged battery and the same battery in use is described by the state of charge of a battery. It has something to do with the amount of electricity left in the cell. It is calculated by dividing the remaining charge in the battery by the maximum charge that the battery can give. As shown below, it is expressed as a percentage.

$$\mathrm{SOC} = \frac{(Q_0 + Q)}{Q_{\max}} \times 100\%$$

where Q_0 represents the initial charge of the battery, Q corresponds to the quantity of electricity.

The state of health (SoH) of a battery describes the difference between a researched battery and a new battery while also taking into account cell aging.

It's the proportion of a battery's maximum charge to its rated capacity. As shown below, it is expressed as a percentage.

$$\mathrm{SOH} = \frac{Q_{\max}}{C_r} \times 100\%$$

whereas $Q_{\max}$ represents the maximum charge availability of the battery, C_r corresponds to the rated capacity.

5 How ML Algorithms Appropriate in SOH Estimation

Feng et al. [9] introduced partial charging segment based on support vector machine (SVM) for estimating online SOH on Lithium-ion battery. Also this work describes the institution of SVM model for new cell in battery with linear programming along with its parameter finding for all SOH via least square method. Feng et al. [10] detecting parameter inconsistency. Aloisio et al. [11] applied several machine learning algorithms like KNN, LDA, NB, Decision tree and Support vector machine for estimating SOH in Li-ion battery. Andre et al. [12] proposed SVM approach, dual Kalman filter method for estimating SOC and SOH on Li-ion battery. These two approaches were confirmed and validated via cell capacity in cycle form, cycle aging tests and capacity of battery. Man-Fai et al. [13] and Zou et al. [14] determined that basic machine learning algorithms appropriate for evaluating SOC and SOH in battery which are used in electric vehicles. Kim et al. [15] utilized reinforcement learning approach for predicting SOC for Li-ion battery. Using this reinforcement learning the features gets reduced by improved Kalman filter technique which is an iterative approach.

Roman et al. [16] built machine learning model based on pipeline for battery capacity prediction. For that battery capacity prediction, metric such as health of battery with 179 cells succession below several situations. The proposed pipeline based on ML algorithms evaluated SOH in linked with assurance gap via both parametric and non-parametric algorithms. Wang et al. [17] deduced that machine learning algorithms helpful in predicting SOC in Li-ion battery where some other algorithms were not supported during decoding because of non-linear problem. That SOC estimation in Li-ion battery was found in Hi-Fi range which means high quality and high capacity of battery too. Vidal et al. [18] reviewed several articles based on usage of machine learning technique for estimation of SOC and SOH in electric vehicle battery.

6 Deep Learning Techniques Suitable in Battery Health and Charge Estimation

Anjum et al. [19] designed deep learning-based neural network framework along with its hyper-parameter settings to efficiently evaluate SOC in electric vehicle battery cells. The layers in neural network and also neurons may diminish the computational

Fig. 3 Architecture of DL for SOC estimation proposed by [19]

costs, sources needed with no cooperation in performance. The framework of deep learning proposed by [19] for SOC estimation in E-vehicle battery is depicted in Fig. 3.

Venugopal et al. [20] built recurrent Neural Network for predicting SOC in battery especially Li-Nickel cobalt aluminum oxide battery. Liu et al. [21] introduced deep learning techniques and ultrasonic sensors for observing every states of battery. Metrics like Root Mean Square Error were estimated to predict the learning rate by the way states of battery was analyzed. Khan et al. [22] introduced NN for SOH estimation on lithium battery. Vidal et al. [23] proposed deep learning-based transfer learning especially LSTM-RNN approach for estimating SOC in Li-ion battery. Also, Kalman filter technique was utilized for testing, developing DL algorithms, and design the filter for every battery type. The structure of Li-ion battery proposed by [23] using LSTM-RNN is depicted in Fig. 4.

Gao et al. [24] proposed novel method by considering side reactions more lifetime of Li-ion corrupted battery for estimating SOC and SOH of battery. Zhang et al. [25] applied enhanced Radial Basis Function-based neural network model for SOC estimation of Li-ion battery pack.

Wei et al. [26] applied the integration of LSTM along with exogenous input neural network for estimating SOC in Li-ion battery which helps to solve the issues of gradient descent and gradient explosion by means of self-regressive approaches. The performance of the NN model was estimated through RSME evaluation by the way the Li-ion battery estimation was identified. The optimization NN method was utilized by Lipu et al. [27] for SOC assessment in Li-ion battery. The configuration is shown in Fig. 5.

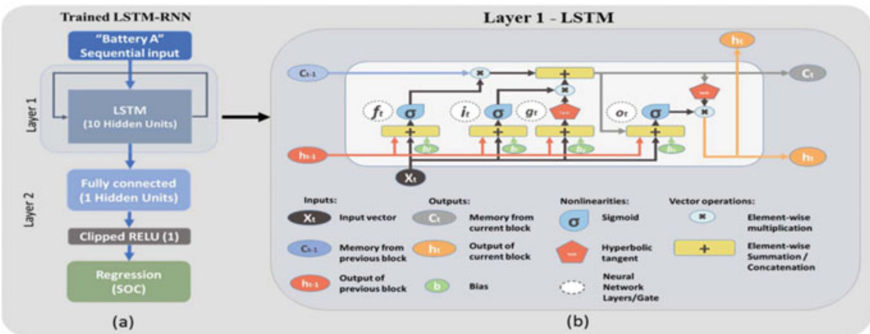

Fig. 4 Framework designed by [23] using hybrid method LSTM-RNN for SOC prediction

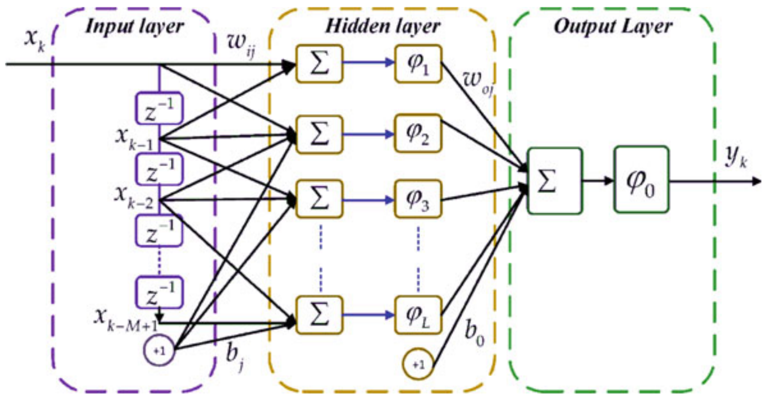

Fig. 5 The configuration on Neural Network based on time delay for estimation of SOC of Li-ion battery

Li et al. [28] proposed layers involved in Convolutional Neural Network method found the capacity of battery which is longer lifetime and fast too. This paper follows three phases such as sequence to image conversion, data separation and finally CNN design for estimating battery capacity. Also, based on RMSE value the model performance in finding capability of battery was estimated.

Shi et al. [29] applied hybrid approach includes deep learning based algorithm along with advanced Kalman filter method for finding SOC and SOH with highly optimized in Li-ion battery. Based on the findings of Mean square error, the performance of deep learning model was analyzed in SOC and SOH prediction for Li-ion battery.

7 Survey Table on Techniques Used, Battery Estimation, Advantages

In this section, we are discussing the techniques used, what kind of battery, battery estimated especially SOC/SOH, metrics used, and accuracy in percentage are summarized in Table 2.

8 Conclusion

In this survey, we reviewed several articles to highlight their achievability and also environmentally friendly in production with health of battery in reality. We discussed the basic concepts of battery, cells, and different kinds of battery such as rechargeable and non-rechargeable along with its characteristics. We surveyed how machine

Table 2 Overall survey table comprises of techniques used, what kind of battery, battery estimation by various researchers, metrics evaluated by each work and accuracy in percentage

Survey work	Techniques used	Kind of battery	Battery estimation (SOC/SOH)	Metrics found	Accuracy
Aloisio et al. [11]	Both classification (SVM, DT, KNN, NB) and Regression model	Li-ion batteries	SOH estimation	R^2 and Mean Absolute Error	91.5%
Zhang et al. [25]	RBF-NN	Li-ion battery pack	SOC estimation	Root Mean Square Error, Max Absolute Error	RMSE = 0.08
Erlangga et al. [2]	Coulomb counting method along with dual Kalman	Lithium battery	SOC and SOH estimation	–	Error below 1% only
Feng et al. [9]	Support Vector Machine	Li-ion battery	SOH estimation	Partial charging segments	Error less than 2%
Guo et al. [3]	Dual extended Kalman filtering approach	Electric vehicle battery	SOH estimation	Accuracy	Greater accuracy with less error
Andre et al. [12]	SVM with dual filter	Li-ion battery	SOC and SOH estimation	Open current voltage curve, pulse power method	Error less than 1%
Vidal et al. [23]	LSTM-RNN along with transfer learning	Li-ion battery	SOC estimation	Accuracy	Maximum accuracy
Fan et al. [5]	Open circuit voltage	Li-ion battery	SOH estimation	–	Capacity error less than %
Gao et al. [30]	Side reactions	Li-ion degraded battery	SOC and SOH estimation	Determining error	Estimating states of battery
Kim et al. [15]	Reinforcement learning	Li-ion battery	SOC estimation	Finding reward value	Error reduction
Wei et al. [26]	LSTM and NARX NN model	Li-ion battery	SOC estimation	RMSE	Less than 1%
Wang et al. [17]	Machine learning	Li-ion battery	SOC	Finding estimation error	Less than 1%
Roman et al. [16]	Machine learning pipeline	Li-ion battery	SOH estimation	RMSE	RMSE error is 0.45%

(continued)

Table 2 (continued)

Survey work	Techniques used	Kind of battery	Battery estimation (SOC/SOH)	Metrics found	Accuracy
Lipu et al. [27]	Neural Network	Li-ion battery	SOC estimation	RMSE	<1%
Man Fai et al. [13]	ML	E-vehicle battery	Both SOC and SOH	Throughput	High
Shi et al. [29]	Hybrid (DL + Kalman filter)	Li-ion battery	Both SOC and SOH	Error estimation	Less error rate 1.4%
Li et al. [28]	CNN	Li-ion battery	Estimation of battery capacity	RMSE	<0.02%

learning and deep learning-based algorithms appropriate in SOC and SOH estimation for batteries especially Li-ion battery which are utilized in electric vehicles. Moreover, the techniques used by several researchers, what kind of battery, estimation of state of health and state of charge, metrics used for finding the performance of the model, and finally accuracy percentage were summarized as survey table.

References

1. Caliwag AC, Lim W (2019) Hybrid VARMA and LSTM method for lithium-ion battery state-of-charge and output voltage forecasting in electric motorcycle applications. IEEE Access. https://doi.org/10.1109/ACCESS.2019.2914188
2. Erlangga G, Perwira A, Widyotriatmo A (2018) State of charge and state of health estimation of lithium battery using dual Kalman filter method. In: The 2018 international conference on signals and systems (ICSigSys). IEEE
3. Guo Q, Qu W, Deng H, Zhang X, Li Y, Wang X, Yan X (2017) Estimation of electric vehicle battery state of health based on relative state of health evaluation
4. Lin C-H, Wang C-M, Ho C-Y (2016) Implementation of state-of-charge and state-of-health estimation for lithium-ion batteries. In: IECON 2016—42nd annual conference of the IEEE industrial electronics society, pp 4790–4795. https://doi.org/10.1109/IECON.2016.7793672
5. Fan J et al (2019) IOP Conf Ser J Phys Conf Ser 1187:022014. IOP Publishing. https://doi.org/10.1088/1742-6596/1187/2/0220
6. Noura N, Boulon L, Jemeï S (2020) A review of battery state of health estimation methods: hybrid electric vehicle challenges. World Electric Veh J 11:66. https://doi.org/10.3390/wevj11040066
7. How DNT, Hannan MA, Hossain Lipu MS, Ker PJ (2016) State of charge estimation for lithium-ion batteries using model-based and data-driven methods: a review. IEEE Access 7:136116–136136. https://doi.org/10.1109/ACCESS.2019.2942213
8. Li Y, Liu K, Foley AM, Zülke A, Berecibar M, Nanini-Maury E, Van Mierlo J, Hoster HE (2019) Data-driven health estimation and lifetime prediction of lithium-ion batteries: a review. Renew Sustain Energ Rev 113:109254. https://doi.org/10.1016/j.rser.2019.109254
9. Feng X, Weng C, He X, Han X, Lu L, Ren D, Ouyang M (2019) Online state-of-health estimation for li-ion battery using partial charging segment based on support vector machine. IEEE Trans Veh Technol 1–1. https://doi.org/10.1109/tvt.2019.2927120

10. Feng F, Hu X, Hu L, Hu F, Li Y, Zhang L (2019) Propagation mechanisms and diagnosis of parameter inconsistency within li-ion battery packs. Renew Sustain Energ Rev 112:102–113
11. Aloisio D, Campobello G, Leonardi SG, Sergi F, Brunaccini G, Ferraro M, Antonucci V, Segreto A, Donato N (2020) A machine learning approach for evaluation of battery state of health. In: 24th IMEKO TC4 international symposium 22nd international workshop on ADC and DAC modelling and testing IMEKO TC-4 2020
12. Andre D, Appel C, Soczka-Guth T, Sauer DU (2013) Advanced mathematical methods of SOC and SOH estimation for lithium-ion batteries. J Power Sour 224:20–27. ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2012.10.001
13. Ng M, Zhao J, Yan Q, Conduit G, Seh Z (2020) Predicting the state of charge and health of batteries using data-driven machine learning. Nat Mach Intell 2:161–170
14. Zou Y, Hu X, Ma H, Li SE (2015) Combined state of charge and state of health estimation over lithium-ion battery cell cycle lifespan for electric vehicles. J Power Sour 273:793–803. ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2014.09.146
15. Kim M, Kim K, Kim J, Yu J, Han S (2018) State of charge estimation for lithium ion battery based on reinforcement learning. IFAC-PapersOnLine 51(28):404–408. https://doi.org/10.1016/j.ifacol.2018.11.736
16. Roman D, Saxena S, Robu V et al (2021) Machine learning pipeline for battery state-of-health estimation. Nat Mach Intell 3:447–456. https://doi.org/10.1038/s42256-021-00312-3
17. Wang W, Brady NW, Liao C, Fahmy YA, Chemali E, West A, Preindl M (2019) High-fidelity state-of-charge estimation of li-ion batteries using machine learning. arXiv:abs/1909.02448
18. Vidal C, Malysz P, Kollmeyer P, Emadi A (2020) Machine learning applied to electrified vehicle battery state of charge and state of health estimation: state-of-the-art. IEEE Access. https://doi.org/10.1109/ACCESS.2020.2980961
19. Anjum M, Asif M, Williams J (2021) Towards an optimal deep neural network for SOC estimation of electric-vehicle lithium-ion battery cells. In: Mporas I, Kourtessis P, Al-Habaibeh A, Asthana A, Vukovic V, Senior J (eds) Energy and sustainable futures. Springer proceedings in energy. Springer, Cham. https://doi.org/10.1007/978-3-030-63916-7_2
20. Venugopal P, Vigneswaran T, Sofana Reka S (2021) State of charge estimation of lithium batteries in electric vehicles using IndRNN. IETE J Res. https://doi.org/10.1080/03772063.2021.1906770
21. Liu C (2018) Battery states monitoring using deep learning and ultrasonic sensors. CS230, Deep learning, Winter 2018. Stanford University, CA
22. Khan N, Ullah FUM, Afnan, Ullah A, Lee MY, Baik SW (2021) Batteries state of health estimation via efficient neural networks with multiple channel charging profiles. IEEE Access 9:7797–7813. https://doi.org/10.1109/ACCESS.2020.3047732
23. Vidal C, Kollmeyer P, Chemali W, Emadi A (2019) Li-ion battery state of charge estimation using long short-term memory recurrent neural network with transfer learning
24. Gao Y et al (2018) Estimation of state-of-charge and state-of-health for lithium-ion degraded battery considering side reactions. J Electrochem Soc 165(16):A4018
25. Zhang L, Zheng M, Du D, Li Y, Fei M, Guo Y, Li K (2020) State-of-charge estimation of lithium-ion battery pack based on improved RBF neural networks. Hindawi Complexity 2020:10. Article ID 8840240, https://doi.org/10.1155/2020/8840240.
26. Wei M, Ye M, Li IB, Wang Q, Xu X (2020) State of charge estimation of lithium-ion batteries using LSTM and NARX neural networks. IEEE Access. https://doi.org/10.1109/ACCESS.2020.3031340
27. Hossain Lipu MS, Hannan MA, Hussain A, Ayob A, Saad MHM, Muttaqi KM (2020) State of charge estimation in lithium-ion batteries: a neural network optimization approach. Electronics 9:1546. https://doi.org/10.3390/electronics9091546
28. Li Y, Li K, Liu X, Zhang L (2020) Fast battery capacity estimation using convolutional neural networks. Trans Inst Meas Control 014233122096642. https://doi.org/10.1177/0142331220966425

29. Shi Y, Ahmad S, Tong Q, Lim TM, Wei Z, Ji D, Zhao J (2021) The optimization of state of charge and state of health estimation for lithium-ions battery using combined deep learning and Kalman filter methods. Int J Energ Res 45(7):11206–11230. https://doi.org/10.1002/er.6601
30. Gao T, Lu W (2021) Machine learning toward advanced energy storage devices and systems. iScience 24(1):101936. https://doi.org/10.1016/j.isci.2020.101936