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A Comprehensive Review of Available Battery Datasets, RUL Prediction Approaches, and Advanced Battery Management

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ABSTRACT Battery ensures power solutions for many necessary portable devices such as electric vehicles, mobiles, and laptops. Owing to the rapid growth of Li-ion battery users, unwanted incidents involving Li-ion batteries have also increased to some extent. In particular, the sudden breakdown of industrial and lightweight machinery due to battery failure causes a substantial economic loss for the industry. Consequently, battery state estimation, management system, and estimation of the remaining useful life (RUL) have become a topic of interest for researchers. Considering this, appropriate battery data acquisition and proper information on available battery data sets may require. This review paper is mainly focused on three parts. The first one is battery data acquisitions with commercially and freely available Li-ion battery data set information. The second is the estimation of the states of battery with the battery management system. And third is battery RUL estimation. Various RUL prognostic methods applied for Li-ion batteries are classified, discussed, and reviewed based on their essential performance parameters. Information on commercially and publicly available data sets of many battery models under various conditions is also reviewed. Various battery states are reviewed considering advanced battery management systems. To that end, a comparative study of Li-ion battery RUL prediction is provided together with the investigation of various RUL prediction algorithms and mathematical modelling.

INDEX TERMS Battery datasets, battery data repository, remaining useful life (RUL), battery management, li-ion battery, RUL prediction methods.

I. INTRODUCTION

Energy storage has become one of the predominant sectors as most of the consumer electronics are powered with battery-like technologies and electricity generation is rapidly growing from renewable energy sources [1]. As the generation of electricity is rapidly increasing from non-predictable and variable sources, the energy scenario is changing significantly. The increasing degradation of the energy market in developing countries, changing in the transportation sector also responsible for the rapid awareness about energy storage [2]. The energy storage technology can be categorised as:

1) Electrochemical storage for short storage time and high efficiency, such as battery technology.
2) Mechanical storage for large capacity and power, such as compressed air energy storage.
3) Chemical storage for low efficiency but long storage periods, such as hydrogen and methane.
4) Thermal storage for high efficiency and long lifetimes, such as storage of thermochemical energy, storage of sensible heat, and storage of latent heat [3].

Among this rechargeable electrochemical storage or battery technology is most commonly seen for its application. A battery converts electrochemical energy to electricity and serves as a portable power supply that is small in size and can be placed anywhere. Mostly used battery cells are Lead Acid cells, Redox Flow cells, Sodium Sulfur cells, and Lithium-Ion cells.

Lithium-ion batteries are preferred over other battery technologies in various application due to long lifetime, huge potential density, lighter weights, and less self-discharge. Such applications include aircraft, electric vehicles (EV), satellites, marine systems, mobiles, laptops, and other consumer electronics [4], [5]. This massive demand for Li-ion battery cells has meant that it is essential to evaluate their reliability. In this regard, comprehensive research is focused on the management of charging and discharging, estimation of remaining useful life (RUL), and characterisation of the performance degradation of Li-ion batteries (LIB) [6]–[8]. The accidental failure of Li-ion cells due to performance degradation and many unforeseen reasons may lead to catastrophic failure, operational impairment, exposure, and performance degradation [8]–[10].

Although Li-ion batteries are preferred over other battery technologies for their lightweight, high energy storage, low charge loss, no requirements of complete discharge, and a great amount of charge and discharge cycles. But it also has various disadvantages. The most considerably, li-ion batteries have a short lifetime, fast degradation rate, ruined if they are completely discharged, more costly, and risk of getting busted to flames is more compared to other existing battery technology [11]. Many accidents have occurred over the last decade due to the failure of LIB. Table 1 shows the accidents in chronological order. Such incidents emphasise the importance of RUL prediction and proper management for LIB.

To overcome the limitations of current LIB technology advance battery management may be helpful. For better battery management and RUL prediction, it is important to choose carefully the most appropriate datasets. As research on Li-ion battery is one of the trending research topic, many organizations have provided data sets for a variety of battery models. Using these data-sets may provide better results in the estimation of battery states and RUL prediction, and the use of these data-sets will save the time of building new data sets. Better knowledge of data sets may also improve battery management by improving the accuracy of battery state estimation. Figure 1 describes the process of data acquisition for RUL prediction for LIB. First, the specific battery cell is selected, and reliable parameter data is acquired with the help of measuring elements. This data is used for the construction of health indicators, which later facilitate the estimation of RUL.

Performance state estimation and life prediction have become a vital issue in battery management and it's use [19]. Figures 2 and 3 illustrate the number of publications on RUL estimation for LIB over the last decade. As reflected in those figures, the number of publications increases gradually

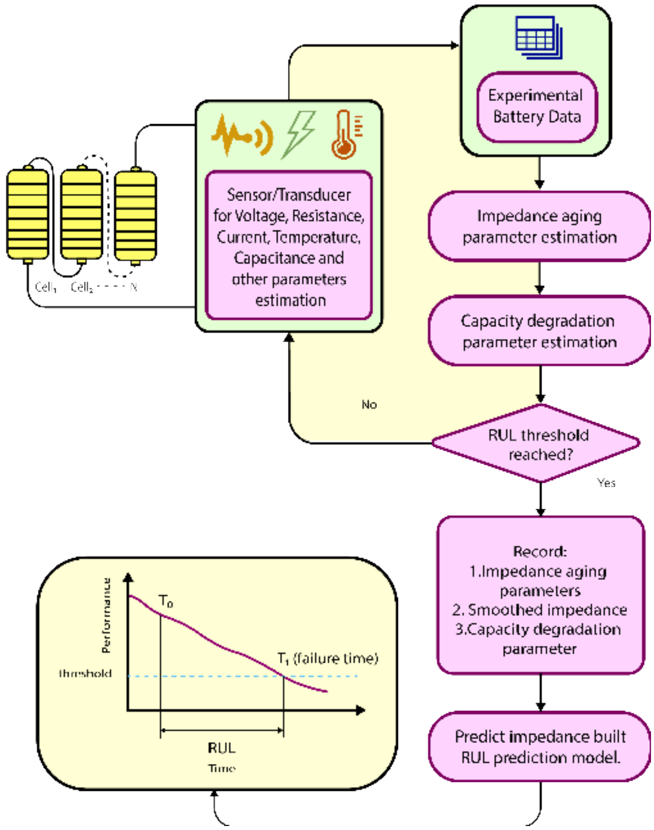

FIGURE 1. Li-ion battery data acquisition to RUL prediction process

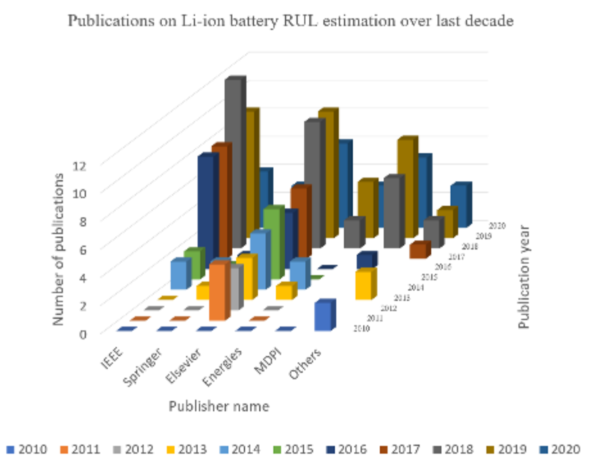

FIGURE 2. Publications on Li-ion battery RUL estimation over the last decade

(the highest percentage of publications is in the IEEE journals, obviously due to the relevance of the subject), which reinforces a need for a complete literature review. Gu et al. [19] reviewed techniques for battery life modeling and provided a summary of the characteristics of each model and their typical applications. Later, Xing et al. [20] provided a contrasting review of reliable prediction-based methods for LIB. They discussed some major issues in battery reliability with the investigation of procedures in health observation and life prediction of batteries and also conducted a comparative

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TABLE 1. Accidents occurred due to faults in battery management

Sl. No	Accidents Description	Year	Reference
1	Two nano iPods overheated and caught fire in Japan.	March, 2010	[12]
2	The batteries of an Acer 2700 personal laptop batteries burnt out as a result of overheating of the Li-ion battery.	April, 2010	[12]
3	An EV taxi caught fire in China due to a short circuit	April, 2011	[13]
4	An embargo on the global transporting of products with Li-ion cells was cancelled by the U.S. Postal Service. The embargo had been placed on the account of fears of short circuits, Which could lead to a fire in the cargo section of aeroplanes	May, 2012	[14]
5	Six Tesla S cars caught fire as a result of self-ignition due to a short-circuit of Li-ion cells.	November, 2013	[15], [16]
6	Many explosions occurred due to limited room among the battery and other parts in the Samsung Note 7 smartphone.	2016	[17]
7	An electric scooter in China caught fire and blew up during charging.	July 29, 2018	[18]
8	Another case of battery self-ignition was reported while charging the Samsung Galaxy S10 mobile phone.	2019	[15]

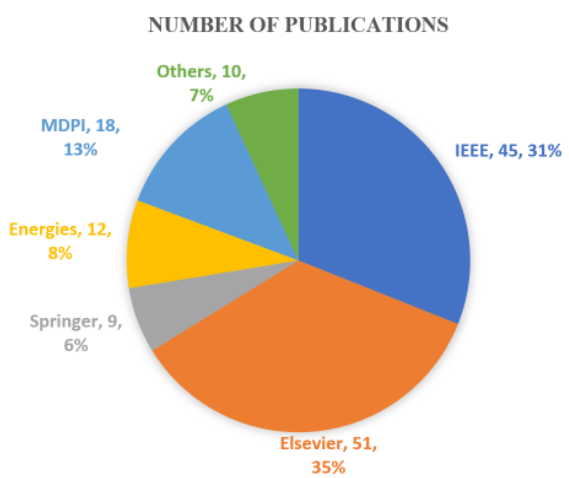

FIGURE 3. Total number of publications in various journals, related to Li-ion battery RUL estimation over the last decade

study of many different methods and measurements for LIB. Zhang and Lee [21] reviewed LIB fitness developments, summarizing a few algorithms that were applied for state-of-charge prediction, remaining-useful-life estimation, and other battery reliability aspects (voltage, capacitance, etc.). Watrin et al. [22], in their literature review, presented three adaptive systems: Kalman Filter, the ANN (Artificial Neural Network), and the Fuzzy Logic systems to State of Charge (SOC) and State of Health (SOH) approximation for LIB. Meanwhile, [23] reviewed aspects of development and research on LIB aging and prediction in multiple fields. They also provided a synopsis of methods, algorithms, and models used for battery RUL prognosis and SOH approximation with a comprehensive electrochemical approach to statistical methods dependent on data. The same year, [24] published a review on applications and enhancement algorithms of using a support vector machine (SVM) to estimate RUL. Those reviews were comprehensive at the time of publication, but the rapid extension of research on LIB RUL prognosis in the past few years necessitates further review. A literature review of generic prognostic approaches was conducted by [25] in which the authors advocated using hybrid prognostic approaches and determined the advantages of related prognostic methods to estimate the RUL of various engineered systems. Concerning EV cells, Rezvanizaniani et al. [26] evaluated prediction strategies to ensure EV safety and mobility. A review of LIB using SOH estimation approaches was conducted by [27] who did not consider RUL estimation. Lipu et al. [28] drew the inference of a simple analysis on the RUL and SOH prognosis of Li-ion cells in EVs. The data-driven health estimation and health prognosis of Li-ion cells were reviewed by [29]. Meng and Li [30] conducted a literature review on prediction and health management (PHM) techniques of Li-ion cells in 2019. In the following year, depending on the classification framework Z. Zhao [31] reviewed the SOH of Li-ion batteries and discussed the aging reasons LIB. They introduced the SOH prediction method along with the analysis of the main advantages and drawbacks of each technique. However, the review was confined to SOH and aging rather than RUL estimation.

Figure 4 illustrates the summary of all current and past reviews of RUL prediction for LIB. As illustrated by that figure, it is quite evident that a more updated and comprehensive analysis of battery RUL prognosis is necessary with more advanced battery data acquisition. Consequently, the aim (and therefore the contribution) of this review is also highlighted in Figure 4. There exist a few review articles regarding battery state estimation and RUL prediction, and mostly they are focused on a smaller field, e.g., only the discussions of the state of health or RUL prediction.

This article merges the review of battery data sets with

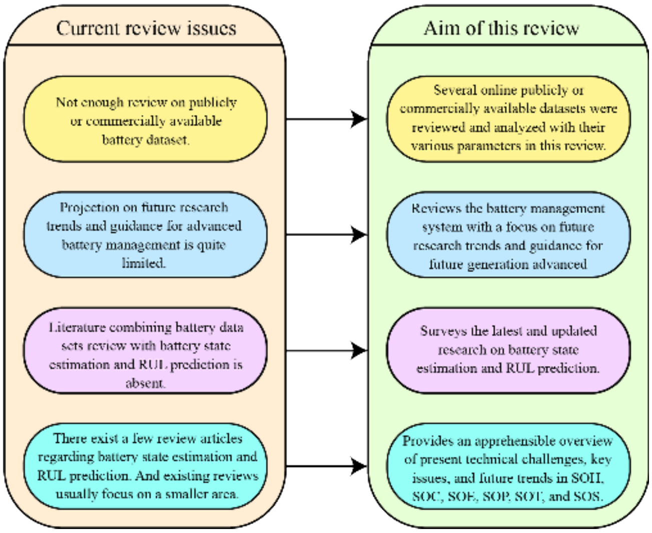

FIGURE 4. A comparison of the current review issue and aim of this review

battery state estimation and battery RUL prediction review. For starting research in battery proper battery dataset selection is essential, one of the aims of this review is to review publicly and commercially available battery data sets. This may help to choose appropriate datasets for battery research and the use of these data sets can save the time of generating new. Simultaneous review of both battery management and battery RUL prediction in a single article helps to diagnose the correlation between BMS and RUL. This also helps to understand the difference between various battery states and RUL with the conjunction of actual commercial and industrial conditions. At a time, review of battery data sets, battery management, and RUL prediction feasibly helps to visualize the causes of battery performance degradation and aging.

Consequently, the focal point of this review is to provide a comparative study of battery RUL estimation procedures including battery management and provide sufficient information on commercially and freely available online battery data sets.

The rest of this article is ordered as follows section 2 discusses data acquisition of commercially available online data sets for LIB; their introduction, properties, and application; and providing a comparison of the data sets. A summary of battery management systems is given in Section 3. The principal RUL prediction approaches are discussed in Sections 4 and 5; along with general RUL prediction techniques and a comparison of terms. Section 6 proposes future research on battery management and RUL prediction.

II. DATA ACQUISITION AND AVAILABLE LI-ION BATTERY DATA SETS

Data plays an essential role in prognostic modeling. In the data acquisition process, are range of monitoring data are captured and stored from many sensors [32]. The internet has dramatically increased the availability of data which can also be used for software simulated data. However, to acquire real-time data, a data acquisition system must be built. Jamshidi et al. [33] used a data set provided by NASA scientists (developed from a range of trials on 18650 Li-ion batteries) to model a small satellite LIB using a neuro-fuzzy based black-box technique.

Figure 5 highlights the basic information to generate simulated battery data–the battery should energize the electric motor that will move the drill, requiring the use of the current and voltage of the batteries. Using the data acquisition card, the data set can be generated in MATLAB. This data was experimental but a data set can be simulated using a real-time computer that contains an EV model for which the vehicle network toolbox helps to communicate with the real-time computer. The battery energizes the EV model and the voltage and current degradation are generated through the data acquisition card.

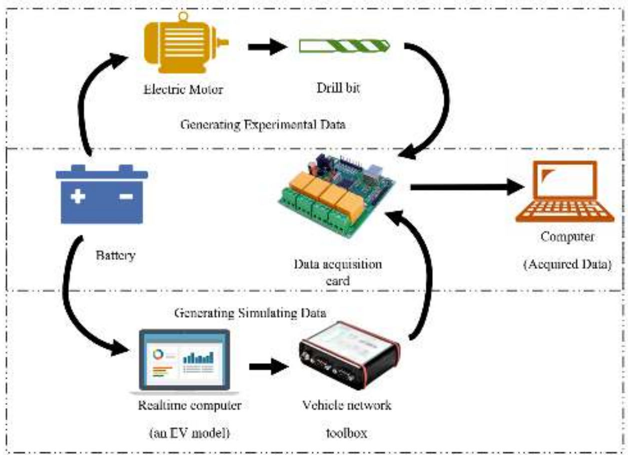

FIGURE 5. Generating experimental and simulating battery data

Several data sets have been published over the years due to increasing research in battery technology, especially in Li-ion batteries. These data sets are available online, and most are free to use in research under some conditions. These battery data sets are built using a range of battery models and can be useful for estimating many battery states for example State of Health (SOH), State of Safety (SOS), State of Charge (SOC), State of Temperature (SOT), State of Power (SPO), and State of Energy (SOE) under a range of conditions. Determining these states is necessary to support better battery management and RUL prediction. The following are some available online data sets, which are discussed with their properties and applications.

A. TOYOTA RESEARCH INSTITUTE

1) Introduction to the data set

Under fast charging conditions, this data set provides 124 commercial Lithium-ion batteries cycled to their failure. The Lithium-ion phosphate/graphite cells were made using the A123 System and cycled in a forced convection temperature chamber set to 30 degrees centigrade in horizontal cylindrical fixtures of battery testing potentiostat. These cells have a professed electromotive force of 3.30 V and a professed capacity of 1.1 Ah. The purpose of this data set is to optimize fast charging for Li-ion batteries in which all battery cells are charged with one or two steps of fast-charging. This policy conforms to the ordination of "C1(Q1)-C2", where C1 and C2 are the initial and following perpetual-current steps in the given order. State of Charge is indicated in percentage by Q2 at which rate the currents change. The cells charge at 1C CC-CV, and the second current step C2 finishes at 80 percent of the State of Charge. 3.6 V and 2.0 V are the top and bottom cut-off voltage, and this is consistent with the manufacturer's specification. These cut-off voltages are fixed for all current steps. The cells may exceed the above cutoff voltage at the time of fast charging after some cycling, which leads to a significant constant-voltage load. At 4C, all batteries are discharged.

2) Data set properties

1) The dataset is categorised into three "batches," which represent about 48 battery cells in every division, and a "batch date" defines each batch. However, there are some irregularities in each batch.
2) The data is given both in MATLAB and Python format. A MATLAB struct is available for each data batch. The information for each cycle is easily accessible by the struct, which provides a convenient data container. This struct can be accessed in both MATLAB and Python format with the h5py package. Further, code is also provided by which Pandas data frames can be generated. The provisional data for every cell is available in a CSV file, however, in either experiment time or step time in which the experiment time resets to zero mid-cycle, the CSV files occasionally have errors, and these errors are subdued.
3) Kapton was taped to the exposed cell using thermal epoxy (OMEGATHERM 201), and after removing a tiny portion of the plastic isolation, a T category thermocouple was attached to measure the temperature. However, the thermal communication between the thermocouple and the battery cell varied, and the thermocouple sometimes failed to communicate during cycling–consequently, the temperature measurements are not entirely reliable.
4) The internal resistance measurements were obtained at the time of 80 percent charging of SOC and around ten pulses of ±3.6C having a pulse width of 30-33 ms.

3) Data set applications

The authors of this data set used the data in their publication on the data-driven prognostic of battery cycle life ahead of capacity abasement [34].Although the dataset was only published in 2019, it has already been cited in about 116 research works. Ma et al. [35] used this data set in their research in the RUL prognosis of Li-ion cells in which they proposed a hybrid neural network with a false nearest neighbour technique. Also using this data set, [36] proposed the exact forecasting of the SOH of Li-ion cells which was attained with a crossbreed model. The model was established with the help of the Elman neural network (NN) and the auto-regressive moving average (ARMA) model. Lucu et al. [37], in a two-paper series, developed a data-driven aging model for LIB under the Gaussian Process framework using this data set.

B. MENDELEY

1) Introduction to the data set

These data sets may be applicable to examine Neural Network and Kalman Filter based SOC methods or to build up battery models. According to the publisher, the data sets are usable as a reference so researchers can make a comparison of their models and techniques role for a fixed data set. A series of tests were performed, at five different operating temperatures, on a 2.9Ah Panasonic 18650PF battery in an eight cu.ft. temperature compartment having a 25A, 18V Digatron Firing Circuits Universal Battery Tester channel.

2) Data set properties

1) The experimental data is provided in MATLAB file format.
2) Five pulse discharge HPPC tests (0.5, 1, 2, 4, 6C) were performed at 100, 95, 90, 80, 70..., 30, 25, 20, 15, 10, 5, 0 % of the SOC and the logged data file only includes the pulses (it does not include the subsequent discharges between the pulses). However, if the latter data is needed, the releases between pulses are included in another file, "dis5_10p".
3) Electrochemical Impedance Spectroscope tests were performed from 1mHz to 100, 95, 90, 80, 70..., 30, 25, 20, 15, 10, 5, 0 % SOC.
4) Series of nine drive cycles were performed in the following order: Cycle 1, 2, 3, 4, US06, HWFET, UDDS, LA92, Neural Network (NN). A random mix of US06, HWFET, UDDS, LA92, and Neural Network drive cycles constituted Cycles 1-4. The Neural Network drive cycle LA92 drive cycle was designed to have some new dynamics which may be useful for training neural networks and consists of a combination of portions of the US06. An electric Ford F150 truck with a 35kWh battery pack scaled for a single 18650PF cell was used to calculate the drive cycle power profile.

3) Data set application

The experiment data, or the same type of data, has been used for many publications. Chemali et al. [38], used the data set for the exact SOC prognostic of LIB. An unified approach was developed with a recurrent neural network for exact modelling of Li-ion cell potential and SOC [39]. In [39], the authors analysed the Lithium-ion cell model operation for automotive operating cycles with Electrochemical Impedance Spectroscopy (EIS) parameterization and the current pulse. Additionally, a Battery-Electric Light-Duty

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category 2a Truck, with Crossbred Potential Reserve, was developed and implemented in [40], [41] using these data sets.

C. U.S. GOVERNMENTS OPEN DATA

1) Introduction to the data set

This data set was acquired in NASA's Ames Prognostics Centre of Excellence (PCoE) and taken from a customized battery auguring benchmark. LIB cells were run in a charge, discharge, and Electrochemical Impedance Spectroscopy captured those three operational profiles at different temperatures. The discharges were carried out in various current load stages unless the battery potential was reduced to pre-set potential thresholds. The recommended limit was OEM (2.7 V) to bring about a strong discharge aging result, but some of these thresholds were found to be lower. The test results show that frequent discharge-charge orders cause the fast ageing of cells. The experiments were stopped if cells reached the extermination limit of 30 percent fails in evaluated capacity relative to 2 Ah-1.4 Ah. The data-set can be useful for many applications as the sets are primarily a huge amount of Run-to-Failure time series, and the data can be useful for the upgrade of prediction methods. Additionally, two cells do not have the identical state-of-life at the identical cycle index due to the differences in parameters such as the duration of rest periods, depth-of-discharge (DOD), and intrinsic variability. The target was to capture this uncertainty, which is symbolic of real-life utilization, and construct a reliable estimation of RUL [42].

2) Data set properties

1) The data was acquired from commercial Li-ion 18650 category rechargeable batteries and provided in a MATLAB file.
2) The data cycle is a top-level construction array containing the charge, discharge, and impedance functioning, and the data functioning category can be a charge, discharge, or impedance.
3) Both the date and time of the starting cycle are in the format of a MATLAB date vector.
4) For each charge-discharge fields, the electromotive force is calculated in battery terminal voltage in volts, the calculated current is in Battery output current in amps, the calculated temperature is the battery temperature in degree celsius, the current charge is the calculated current at the charger in amps, the voltage charge is the calculated voltage at the charger in volts and time is a time vector for the cycle (secs).

3) Data set application

Morello et al. [43] used this data set on their report in Li-ion battery aging, providing a preliminary analysis of the obtained results. Other work used this data for effective fault classification for LIB employed in EVs [44].

D. IEEE DATA PORT

1) Introduction to the data set

The data set provides a general and realistic use of electrochemical cells to examine and corroborate standard models and the associated system recognition operation. The data set was gathered automatically utilizing an auto-established programmable battery cycler, that imitates the consumption of electrochemical cells in the naturalistic surroundings of a pure EV. The data was taken by simulating the application of a Li-polymer cell model ePLB C020 in an electric car standardized to the Nissan Leaf. Specifically, the particular cell used for the generation campaign was characterized by an adequate capacity of 15 Ah. To generate the Training Set and the Test Set, two different trips were considered. Both trips were compiled with a mixture of highway, extra-urban and urban driving cycles to find a realistic environment with readjusting and battery charging phases. The test driving cycles were chosen from the Federal Test Procedure depository for practical application of the cell. The Training Set contains a trip of 277.64 km with an amount of about 12 hours of data and the Test Set covers 163.24 km with approximately 7 hours of data. The data was acquired with a sampling time of 1 sec, and SOC succession was assessed employing the Coulomb counting algorithm [45].

2) Data set properties

1) The data is provided in a Zip file, which contains two .mat files called "Training Set.mat" and "Test Set.mat."
2) The data is collected by simulating the use of a Li-polymer cell.

3) Data set application

According to the author, this data set can apply to the SOC calculation, battery health management, and other battery prognostic modeling [45].

E. SCIENCE DIRECT

1) Data set 1

1) Introduction to the data set: The data set provides the Maxwell ultracapacitor behavior and the LiFePO4 type LIB behavior. The urban dynamometer driving schedule rule and the dynamic stress trial state were carried out. This test produced data that promises to clarify the behavior of the ultracapacitors and Li-ion cells and is useful for the assessment of SOC and SOE of the Li-ion batteries and ultracapacitors. This data set includes measured voltage, sampling time, and load current. When discharging the load current is negative and at the time of charging is positive [46].
2) Data set properties:
    a) The data sets were gathered at room temperature.
    b) The data was provided in MATLAB format and acquired from the experiments of Maxwell ultracapacitor and LIFEPO4 type LIB behavior.

3) Data set application: Li et al. [47] used this data set in their research to establish a cloud-based battery management system (C-BMS) and applied a data cleaning approach depending on a ML algorithm towards big data. A review was presented in [48], in which the authors discussed the new SOC estimation methods highlighting the model-dependent, data-driven orderliness. A real-time model-dependent condition monitoring algorithm depending in a 2nd-order RC electrical circuit battery model was suggested by [49] using this data set. [50] recommended an online model for LIB based on condition monitoring. The proposal was established on an electrical circuit battery model with real-time 2nd order capacitor-resistor. The model carries out an increased Kalman filter-based real-time framework pinpointing with an even variable formation filter-based state estimation. Wang et al. [51] use this data set and solve the problem of fractional-order modeling and also worked on the remaining discharge time prognostic of the LIB and ultra-capacitor hybrid potential repository scheme.

2) Data set 2

1) Introduction to the data set: This dataset is about the operating conditions of battery behavior. The battery charging and discharging features were analyzed by dynamic stress test and constant current test. The data set also includes every cell voltage, the total potential of the cell package, and the load current. If the cell is discharged, the load current is negative and is positive at every other time. The data also includes the sampling time. According to the contributors, the data can be used to analyze the dynamic behavior of a battery and also can estimate the battery SOC [46].
2) Data set properties:
   a) The data was provided in MATLAB format.
   b) The LiFePO4 battery was used for the data acquisition.
   c) To show the active actions of the cell pack and state of charge, the capacity and battery properties are provided separately.
3) Data set application: [48] used this data set in their review of the SOC approximation for Li-ion cells in which they mainly focused on model-dependent and data-driven approaches.

F. NASA DATA REPOSITORY

1) Data set 1

1) Introduction to the data set: This data-set was presented by Prognostic CoE at NASA Ames and was acquired by experimenting on LIB [52].
2) Data set properties:
   a) The data set documents the impedance as destruction indicator with charging-discharging in various temperatures.
   b) This data set is provided in MATLAB format (.mat). The data is also in a zip file format.
3) Data set application: The data-set was applied in many research works. Hill et al. [53] used this data to verify the remaining flying period approximation aimed at little electric aircraft. B.Bole et al. [54], adapted an electrochemistry dependent LIB model. The researchers adapted the model for random use. Olivares et al. [55] used this data for the SOH regeneration phenomenon using particle filtering-based prognostics. Some other applications of these data sets include prognostic approaches, RUL estimation, health monitoring of aeronautical batteries, and much other research in [56]–[64]. All publicly and commercially available data-sets are compiled and summarised in Table 2 for a better understanding.

2) Data set 2

1) Introduction to the data set: This NASA repository data was taken from tests aimed at the HIRF cabin of Edge 540 Aircraft [52].
2) Data-set properties: This data is provided in .mat format. The data also in a zip file.
3) Data set application: Hill et al. [53] applied this data to confirm the remaining flying period approximation aimed at little electric aircraft.

G. CALCE BATTERY RESEARCH GROUP

Since LIB promise thousands of cycles, they are attracting increasing research. However, there is limited data available to support the considerable number of studies on this topic. The difficulties of examining the battery cell life cycle are complicated by the combinations of the various elements that affect the life cycle. Those challenges may be overcome with a brute-force approach to testing but, for a range of types of batteries and application disciplines, that kind of experiment requires large quantities of data. The CALCE Battery Research Group tries to put all of those data into one place by describing the kinds of experimentation and battery to provide a better understanding of the complicated relationships among cell design, chemistry, and usage conditions [67].

1) Battery sample- INR 18650-20R

1) Data set description The most essential elements of the battery SOC estimation are low open-circuit voltage (OCV) and incremental current OCV. In this data acquisition, the researchers conducted those two OCV tests for three types of thermal conditions. The SOC approximation is contrasted in terms of accuracy tracking, robustness, and time convergence. For estimator parameter identification and estimator performance evaluation, four dynamic tests were presented [67].
2) Test conditions and properties:

TABLE 2. Publicly and commercially available data sets related to LIB

Data set provider	Data Format	Data info.	Data Category	Reference
TOYOTA Research Institute	.mat/ .py	The battery dataset of Li-ion Phosphate/Graphite cells, consists of 124 commercial LIBs cycled to breakdown data beneath the fast-changing parameters.	Experimental	[34]
Mendeley	.mat	Panasonic 18650PF Li-ion Battery Data. A mint-conditioned 2.9Ah Panasonic 18650PF battery was experimented with an eight cu.ft. temperature room accompanied by a 25.0Amp, 18.0Volt Digatron Firing Circuits Universal Battery Tester channel.	Experimental	[65]
IEEE Data Port	.mat/.zip	Automotive Li-ion cell data set, Li-polymer cell model ePLB C020.	Simulating	[45]
U.S. Government's Open Data	.mat	Li-ion battery aging data set, Commercially usable lithium-ion 18650 sized batteries.	Experimental	[42]
Science Direct	table	LiFePO4 category LIB demeanor and the Maxwell ultracapacitor demeanor.	Experimental	[46]
	table/ .mat/.xls/ .text	data set of operating conditions of battery behavior of the LiFePO4 battery IFP1865140.	Experimental	[66]
CALCE Battery Research Group	.zip/ .xls	Battery parameters data sets, many different battery models.	Experimental Simulating	[67]
NASA Data Repository	.mat	LIB data sets,accumulated from the tests on the Edge 540 Aircraft in High-Intensity Radiated Field room.	Experimental	[52]
	.mat	Li-ion Battery Data. Under various temperatures, the charging and discharging. The damage criterion is the recorded impedance.	Experimental	[52]

a) Low Current OCV: The Low Current OCV test uses a lower current for charging and discharging to keep the corresponding terminal potential in the estimation of OCV. Two data samples are provided at three different temperatures, including initial capacity data.
b) Incremental Current OCV: The incremental current OCV comprises various SOC separations. After that, the OCV with the related SOC was recorder. Two data sets samples are given with different operating conditions.
c) Dynamic test profile: The dynamic test profile consist of a number of active current patterns; Dynamic Stress Test (DST), Federal Urban Driving Schedule (FUDS), Highway Driving Schedule (US06), and Beijing Dynamic Stress Test (BJDST). For each active current parameter, the data is provided at different temperatures for 80 percent battery charge and 50 percent battery charge.
d) Data format: the data is provided in .xls format.

3) Data set application: Zheng et al. [68] applied this data set for online SOC approximation showing the influence of different OCV [68]. A similar application of this data set can be found in [69], where the researchers estimated LIB SOC using OCV at different temperatures. Xing et al. [69] used unscented Kalman filter and neural network modelling by this data set for SOC approximation of Li-ion cells.

2) Battery sample- A123

1) Data set description: Optimal charge/discharge control, SOC approximation, and critical left-over driving grade approximation of EV significantly reliant on the ambient temperature. OCV-SOC do not acts as impartial of environment temperature and generates an error in battery SOC estimation. Despite this, the CALCE Battery Research Group experimented with A123 cells to complete two dynamic tests; the FUDS test and the DST. The data is publicly available on the CALCE research group web page.
2) Test conditions and properties:
   a) Low Current OCV: The data in low current OCV is provided under various operating temperatures from -10 degrees to 50 degrees celsius.
   b) Dynamic profile: Dynamic profile data is also provided at various operating conditions from -10 degrees to 50 degrees celsius.
   c) Data format: Data is provided in .xls format.
3) Data set application: Xing et al. [69] applied the dataset to forecast SOC of Li-ion cells. He et al. [70] also used this data set for unscented Kalman filter (UKF) and neural network modeling (NN) based problem solving for LIB.

3) Battery sample- CS2

1) Dataset description: For this data acquisition, all the CS2 cells were in the same charging profile. The standard current and voltage protocol were applied provided a fixed current scale of 0.5A before the voltage attains 4.2V. After that the 4.2V was kept before the charging current falls down to 0.05A. The discharge

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cut-off voltage was 2.7V. Each CS2 cell was cycled many times.

2) Test conditions and properties:
   a) Data format: Each cell data file contains a collection of files in .xls format, named according to the testing dates.
   b) Data type: Six data types are provided under various operating conditions of cycling.
3) Data set application: He et al. [71] used this data set in their research on Li-ion battery prognostics, applying the Bayesian Monte Carlo method and Dempster-Shafer theory. In [72], the author predicted Li-ion cell RUL with the help of this dataset. Williard et al. [73] also used this data in their analysis of SOH estimation features.

4) Battery sample- CX2

1) Data set description: As with the CS2 battery data set, all CX2 cells also were under a similar charging outline. The graded current and voltage properties were applied provided a fixed current amount of 0.5A before the electromotive force gains 4.2V. After that the 4.2V was kept until the charging current drops under 0.05A. 2.7V was the discharge cut-off voltage. Each CS2 cell was cycled many times.
2) Test conditions and properties:
   a) Data format: Each cell data file contains a collection of files in .xls format, specified observing the experiment dates.
   b) Data type: Six data types are provided under various operating conditions of cycling.
3) Data set application: He et al. [71] used this data set in their research on Li-ion battery prognostic, utilising the Bayesian Monte Carlo procedure and Dempster-Shafer theory. In [72], the author predicted LIBs RUL using this dataset.

5) Battery sample- PL

1) Data set description: Li-ion batteries do not undergo full charging and discharging cycles. The CALCE Battery Research Group performed a test that quantifies the outcome of fragmentary charge-discharge cycling on LIBs capacity dropping. They conducted a cycling test on LiCoO2/ graphite battery with dissimilar SOC scale and discharge currents. Based on the results, they developed a capacity fade model accommodating total or incomplete cycling states. The test result shows graphite/LiCoO2 battery degradation is affected by the mean SOC and also by the improvement in SOC throughout the cycling process. The data from the experiment is available to download from the CALCE web page [67].
2) Test conditions and properties:
   a) The data is provided from eight samples of batteries for different cycling conditions.
   b) The data is provided in a zip file that contains .xls files.
3) Data set application: This data set was used to test cycle life experimentation, and prototyping of Li-CoO2/Graphite batteries in various SOC grades by [74].

6) Battery sample- K2

1) Data set description: For the data acquisition, the tested model was K2-016 and K2-039 battery [67].
2) Test conditions and properties:
   a) The cell was discharged in a fixed current of 2.6A.
   b) The unit voltage during discharge was 4.2V.
   c) Charge at constant voltage unit current was less than 0.08A, and the rest duration was 2 minutes before measuring the resistance.
   d) The data was provided in a zip file containing a .xls file format.

III. BATTERY MANAGEMENT

The large-scale use of Li-ion batteries (LIB) in recent years has encouraged updated algorithms to be developed for the estimation of RUL of LIBs. Many data sets of LIBs for capacity and thermal management [75], SOC calibration [76], detecting fault mechanism [77], neutron imaging [78], voltage [79], and current calibration are being used in research work [80]. Trovò and Andrea [81] described a battery management system (BMS) both in terms of hardware and software for a 9kW/27 kWh Industrial Scale Vanadium Redox Flow Battery. These are, however, directly or indirectly related to battery RUL estimation. Figure 6 illustrates the entire procedure of the battery management process. Various sensors can be used to read the data of battery cells which can be used in data acquisition. These data are used for battery state estimation and controlling of charge and discharge. Based on this information, capacitive and thermal management can be undertaken with various fault diagnoses and cell monitoring. Some BMS (especially for LIB) are discussed below:

Li, Yi, et al. in [82], reviewed the data-driven health estimation methods and RUL prediction approaches. They showed a distinction among ML algorithms applied for SOH assessment of cells and compared the health prediction methods as well. However, their review was mainly focused on battery factors and SOH estimation. In [83], machine learning approaches on BSM were comprehensively studied and provided an overview of machine learning approaches. Though they provided a comparison among ML approaches, the study was mainly focused on BMS.

A. BATTERY THERMAL MANAGEMENT (BTM)

Li-ion BTM is essential to power diligence and is also concerned with thermal protection, improvement of performance, and extending the life cycle. Additionally, proper thermal management also minimizes the temperature gradients between battery cells [84]. Khateeb et al. [85] used

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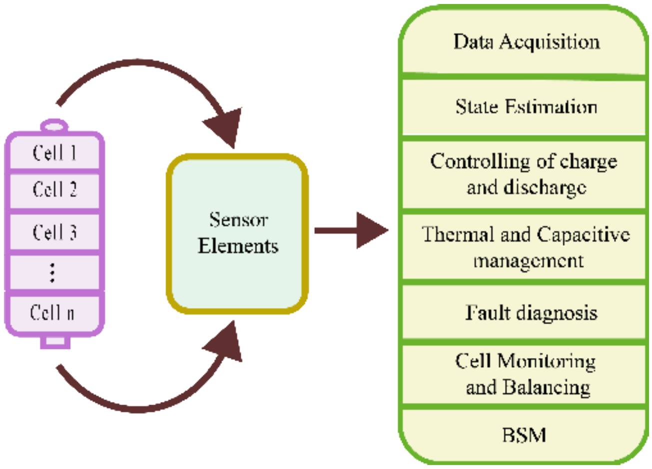

FIGURE 6. Illustration of battery management process

testing ground solutions of a LIB planned for electric scooter diligence. They compared the experimental results of the LIB module (utilizing different heat dissipation systems) between the charge cycle and the discharge cycle. Sun et al. [86] used numerical simulation and experimental setup data for heat transfer enhancement, which was designed to compare the thermal functioning of different BTM Systems. A simulation-based statistical dataset was used to develop a novel BTM system for a tube–shell LIB bundle based on water evaporation (WE) and air-cooling (AC) [87]. Samimi et al. [88] used experimental data to compare the simulating result of the thermal functioning of a LIB cell in the comportment of carbon-fiber phase-change materials composites. Similar work on cylindrical LIB thermal management employing phase transform material composites can also be found in [88].

B. CAPACITY MANAGEMENT

Battery capacity management is essential for SOC, SOH, and RUL prognosis. The use of a battery in EVs requires reliability in cell capacity [89]. Sartini et al. [90] provided a basis for battery capacity measurements and estimated the potential of electrochemical impedance spectroscopy as a diagnostic tool. The research work was completed on a Li-Tec40 Ah li-ion battery presenting AC impedance measurements and measurements in a climate chamber at different temperatures. Yu et al. [91] showed an online capacity estimation method through joint estimation for LIB. The RUL of li-ion battery and degradation process are commonly quantified with capacity or internal resistance. However, duet to complex operational conditions and high costs, these two indicators are not easy to acquire. An innovative health indicator (HI) is imposed from battery current profiles which can be measured directly in online. Based on the extracted HI a relevance vector machine (RVM) algorithm is utilized to make a probabilistic prediction for battery RUL [92]. A novel predicting method for circulating capacity of LIB is suggested considering the effect of random variable current (RVC) on battery capacity degradation. The minimum battery capacity RMSE predicted is 0.010294 and cycle capacity error range is -3mAh to 3mAh [93].

C. BATTERY NEUTRON IMAGING

In the field of engineering for non-destructive testing polychromatic radiation beam applications, Neutron Imaging is used widely [90]. Battery management requires precise prediction of the bulk and the spatiotemporal lithium (Li) concentrations, which is where neutron imaging comes into play. The battery cycle life of more than 1000 cycles would require renewable energy storage. For this, detailed knowledge of the aging and degradation of batteries is required. As demonstrated by [94] during the discharge of an intact industrial battery, a primary anodic reaction and depletion of Lic6 degradation can be observed by neutron imaging. They represented the first attempt in establishing neutron imaging as an insight diagnostic tool for analyzing LIB. Visualizing the migration of Li ions helps to identify areas of reduced activity that are responsible for capacity fading [95]

D. VOLTAGE AND CURRENT CALIBRATION

For better battery management, voltage and current calibration are required. [96] measured the Li-ion battery voltage with a analog to digital transformation. The transformation was power effective. In [97], the parameters influencing battery lifetime were showed for better battery management, and the battery state was calculated. Voltage and current calibration are important for different battery state assessment and this helps in battery management. Those states can be SOC, SOH or others.

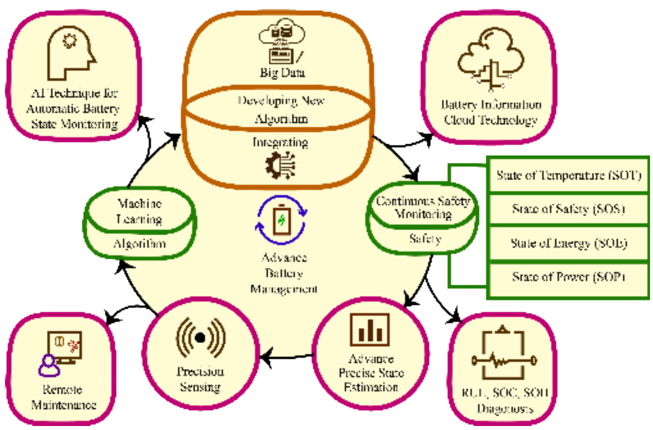

FIGURE 7. Advanced battery management systems

E. PARAMETER ESTIMATION FOR BMS

The battery is not a linear system and it has various complexities, and for this, the BMS depends on various parameters. precise monitoring and estimation of those BMS parameters are cumbersome from a computational perspective. To that end, Figure 7 illustrates different advanced research directions to estimate parameters for BMS. Inarguably, for advance and futuristic BMS, precise monitoring and estimation

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are required for some important terminologies such as SOC, SOH, SOT, and RUL. In this part of the review, the workings of various battery state estimations have been reviewed.

1) Review of SOC and SOH estimation

The way of determining the SOC of batteries can be divided into six processes: 1. Look-up tables process, 2. Coulomb counting process [98], 3. Artificial neural network process [68], 4. Support vector regression process [99], 5. Electrochemical process [100], and 6. Equivalent circuit process [101]. Like the SOC estimation process, the SOH can be categorized into four categories: 1. Physics-dependent models, 2. Empirical process, 3. Models depending on (a) Differential Voltage Analysis (DVA), (b) Incremental Current Analysis (ICA), and 4. Data-driven method [102]. However, various approaches have been proposed for SOC and SOH estimation and much research has been done in this field. Using acoustic-ultrasonic stress wave, precise monitoring of SOH and SOC was introduced in [103]. For the up-gradation of the BMS, advance sensing technology is essential. In [104], an intrinsic co-relation of battery SOH and SOC with waveform signal terminologies was determined using a built-in piezoelectric sensor in the time-domain analysis. Battery cells expand at the time of charging as an outcome of the bumping of battery electrode dynamic material, a strain gauge type extremely precise displacement sensor was used to calculate the generated force of battery cell expansion [105]. Figure 8 illustrates a basic SOH and SOC joint estimation procedure. Firstly, SOH and SOC estimation time update is determined, then this result is feed into an adjustable controller. The update of SOC and SOH is observed.

The ageing of electrode reduces the ability to store energy of batteries and decreases the their lifetime [106]. SOH comprises the ability of a battery to reserve electric energy [107]. Any attributes that defines cell health perhaps usable to characterize SOH as the range explaining battery health condition is so much enlarged. esearch related to characterization of parameters for example power, capacitance, and internal resistance may falsify the true notation of battery health [108]. Battery health depends not only on characterization parameters but internal parameters also. These internal battery health components primarily concern to three influencing apparatus [108]: and these are (i) the loss of active material (LAM), (ii) the loss of conductivity (CL), and (iii) the lithium inventory loss (LLI) [109]. The loss of lithium inventory includes the constitution of lithium dendrites [110], the generation of a solid electrolyte inter-phase layer [111], and the self-discharge of a battery [112]. Active material loss consists of the breakdown of anode material [111], the breakdown of the electrolyte [113], and the breakdown of cathode material [114]. The conductivity loss mainly refers to the battery adhesive to desquamate and degrade. It also consults to the aging apparatus that is responsible for the cell's current collector to collapse and decompose.

To understand cell degradation status in detail, estimation of electrode state of health (eSOH) is essential. The electrode state of health is achieved by utilization range as an eSOH parameter and considering electrode capacity. However, the electrode-specific state of health inside a cell has been given less attention [115]. Electrode-specific state of health gives elaborated information on the degradation status of the battery. Regarding this, it could prevent dangerous battery failure. The existing approaches for eSOH estimation can be categorized in voltage fitting and differential analysis. Voltage fitting finds a parameter set with optimized algorithms. The parameter set gives the best fit between measured data and model prediction for the voltage curve [115]. Using a genetic algorithm, a battery model was proposed with electrode parameters by X. Han et al. [116], and that was identified by fitting the voltage curve. The categorized degradation models for example active material loss and lithium inventory loss [117], were used by Birkl et al. [118] to create a model framework. The framework was applied to perform degradation diagnostics by fitting the model to measured pseudo-OCV data. Both SOC and SOH were estimated using a reduced order electrochemical model, but only the changes in the utilization range were considered [119]. The thermodynamic information from electrode materials is focused on differential analysis focuses. Tracking the changes of distinguishable parameters in differential curves such as differential capacity and voltage curves, degradation diagnosis is performed in differential analysis. The most common type of differential analysis is incremental current analysis [120] and differential voltage analysis [121]. In the differential analysis, the valuable electrochemical parameters become recognizable in the differential data. Xin Lu et al. [122] determined the relationship between electrode aging and the fractional order. They have used the fractional-order as an indicator for electrode aging and a non-destructive way for judging the degradation level of the electrodes of LIBs. A comprehensive study was done by Jun Xu [123], on the mechanical behavior of the electrodes. The study was based on electrochemical conditions and the mechanical loading conditions of batteries.

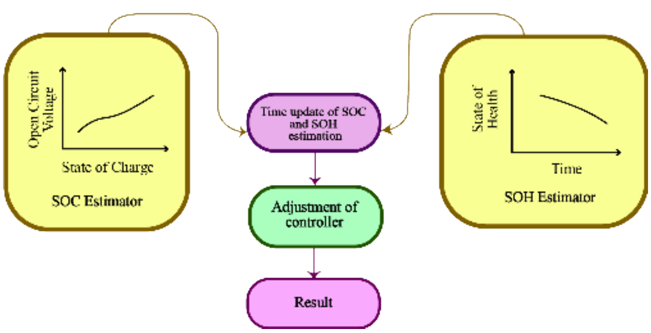

FIGURE 8. Illustration of SOC and SOH joint estimation for BMS.

Future advanced BMS technology can be based on improving and using some upgraded advanced sensing technology, such as holistic state of safety, multi-state joint approximation, scalability, artificial intelligence techniques, and comparative evaluation of various metrics. Multi-state joint esti-

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mation is one of the most promising research directions for BMS [124]. Until now, only a few researchers have addressed multi-state joint estimation (two-state). Most notable is the joint approximation of SOH and SOC. Recently published research papers suggest that the capacity or resistance-based SOH estimation process is important to update the estimation of SOC. Many algorithms such as particle filtering, Kalman filtering, adaptive filtering, non-linear predictive filtering, and extended Kalman filtering have been used to estimate SOH [125]–[128]. These approaches are also important for the two-state joint approximation of the SOH and SOC.

2) Review of SOP, SOE, and SOT Estimation

SOP, SOE, and SOT are the other key parameter estimations required in a BMS. SOP is defined as the usable supply of power by a battery or the engaging power from the system power train in a horizontal period [129]. SOE is another key BMS parameter and several proposals were made for SOE estimation. The most utilized applications are the reliable assumption of the driving mileage in electric vehicles [130], [131]. The estimation of the SOT is still a new concept in BMS, while only a few studies can be found in the literature. [132], [133] provided the internal battery temperature with temperature distribution, from which SOT can be estimated. In [134], both SOC and SOP were used for dual-state joint estimation. Another research shows the hybrid state estimation for SOE and SOP [130]. A co-estimation of state also proposed considering SOP and SOE in [135], [136]. The possibility of multi-state estimations is promising but it still has its limitations [124]. In a real application, more multi-state estimation relationships can be found. However, the current research level only provides three battery state estimation workings [137], [138]. There is considerable scope for further research possibilities in multi-state joint estimation for BMS.

3) Review of SOS Estimation

Previously safety was considered as a system attribute but now it is one of the key issues in system state estimation [124]. SOS is perhaps the most anticipating issue in the field of research on BMS and battery state prognosis [124]. However, the implementation of SOS estimation is changing gradually. Like other common battery states, SOS also provides the battery state information considering safety measurements [139]. In 2020, the thermal runaway phenomena of LIB with computational identification, and safety regime was introduced by internal short circuit test. This made a computational recognition of the safety arrangement of LIB thermal runway [140]. For future work, SOS with other state estimations (SOT, SOE, SOH, SOP, SOC) can be joint and the result of this multi-state joint estimation may provide more accurate and reliable BMS.

Lithium-ion batteries comprises of ignitable components and may go to unpredictable catastrophic failures (CF), together with the release of electrolyte vapors, explosion, fire, and related let out of smoke [141]. During the mechanical loading process, Li-ion batteries experience mechanical deformation leading to an internal short circuit (ISC) that evolves into a thermal runaway (TR). This process involves a transient series of mechanical, thermal, and electrochemical events that evolve with time in a complex manner that has prevented deeper understanding of LIB failure modes [142]. Again, some accidents are caused because of external short circuit (ESC) of batteries. ESC faults can be triggered under any circumstances, for example, deformation of a battery pack during EV collision and water or oil leakage in a battery pack. Once an ESC fault occurs, it may cause a dramatic increase in battery temperature, which would result in thermal runaway [143], [144]. For this, it is necessary to study the thermal behavior of batteries under ESC faults for battery safety management [145]. Li3V2(PO4)3 (LVP) and Li4Ti5O12 (LTO) were chosen as the cathode and the anode to build a full battery in [146] owing to their robust structures. The paper reported that no visible degradation was perceived in both electrodes over 500 cycles. In addition, the relatively high voltage of LTO anode ensures the safe rapid charge and discharge (no dendrite growth) and the minimal or no initial loss of lithium ions as there is no formation of SEI layer. A lot of variables are used to describe the safety of a battery. Castillo et al. [147] presented some variables which are more relevant for a LIB consists of a carbon-based material as negative electrical conductor, and a lithium-metal-oxide material as positive electrical conductor. The listing may differ for different types of energy storage.

1) Temperature: Due to over temperature, the dynamic material and the SEI layer will start to break down. This will result in chances of thermal runaway and exothermic reactions [148], which may cause fire and explosion [149]. And due to low temperature, the reaction rate is significantly reduced. On the negative electrode, the attempt of charge or discharge may cause metallic lithium depositing. This may lead to danger of internal short circuits and permanent loss of capacity [150], [151].
2) Current: Joule heat production is a part of current [152]. In case heat is not discharged faster then the heat generation by a battery. It may cause thermal runway. Another reason of lithium plating is high current charge in the negative electrode and this may cause danger [153].
3) Voltage: Due to over-voltage (over-charge), decomposition is introduced both in electrolyte and the positive electric conductor. This results in the generation of gas and heat [154], [155]. In the negative electrode, the under voltage (over discharge or deep discharge) causes the lithium plating. This also results in dissipation of the copper current gatherer. This can eventually produce copper dendrites, enhancing the probability of internal short circuits [147].
4) SOC: For the increased amount of SOC, a high amount of energy possibly freed as fire or heat at the time of a

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disastrous situation [156]. Therefore, it can be said that SOC and safety are inversely proportional.

5) SOH: In this case two incidents can be noticed. Firstly, an older battery having low SOH won't hold the same amount of charge like a new device. So, it will contain lower SOC which will lower the factor of risk. The second one is an old battery may have signs of lithium plating and swelling or may already contain damage on the separator and the electrodes [147], [153]. As a result, an old battery may be more prone to accidents [153], [157]. Further, the SOH is a significant aspect that must be admitted to thought when thinking about the chances of storage devices 2nd life. The danger demonstrated by the irregular nature of internal short circuits and in the negative carbonaceous electric conductor the metallic lithium plating is significantly risky for second life uses of LIBs. Regarding this, if a sufficient level of safety is assured by the carried-out tests and the aging history is adequately given the aged batteries then only be allowed for further use.
6) Mechanical distortion: Mechanical distortion is obtained by the strain of the battery, by comparing its original dimension to a distorted dimension. It can also be obtained by calculating the stress that could develop such strain. However, the reasons of strain is because of compression or external impacts [147], or may be for ageing and lithium plating [153], or perhaps natural expansion during intercalation [158].
7) Internal impedance: The increase of the SEI layer is typically pointed by a heavy resistance in the negative electric conductor. This increase of SEI section inevitably consumes electrolyte and lithium-ions, which brings down the capacity, this eventually increases the impedance [147]. After manufacturing the cell, when the increase in impedance occurs primarily during the first cycles, SEI layers can be considered stable. The growth of SEI layer remains at the lifespan of system with a shortened rate. The access of the electrode surface for ion intercalation also decreases by the increase in the SEI section. Hereby, it bounds the doing of fast ionic transport while not necessarily decreasing capacity. This results in a power capability reduce. The erosion of electronic and mechanical connection of the electric conductor particles is another source for impedance increase. It works as catalyst in the regular increase and shortening of the carbon framework at the time of intercalation and deintercalation. However, it can also occur because of the binder material decay [159]. Positive electrode may contribute to ageing and increase in impedance because of passivation layer development upon its surface which will reduce the active materials availability. On the other hand, positive electric conductor increments impedance up to 2 to 5 times while compared to the negative electrode [160]. Therefore, impedance changes often demonstrate battery aging by decreasing the battery effectiveness and current capacity each in charge-discharge. Thus, SOC, current rate, and temperature effects and changes the impedance result. Therefore, these conditions should be considered in which the measurements are done.

Overheating, external short circuit, and internal short circuit are the three most common triggers of safety concerns in the operation of Li-ion battery [161]. Any of them can lead to failure of a battery or even an entire battery pack. To ensure the best battery safety and optimal performance SOH calculation and diagnostics is very much crucial. However, the listing above is not final and more variables has to be considered for better evaluation.

Table-3 represent the comparative advantages and disadvantages of various methods used in estimating battery states of LIB.

IV. RUL PREDICTION APPROACHES

RUL is determined as the period when a function of an apparatus decreases to the failure doorstep for the first earliest time [15]. The prognostic method provides information about a system that provides a warning of future failure of the system [189] and is used for the approximation of RUL in various engineered systems such as batteries, EV, and industrial equipment. The RUL of a system or an asset is explained as the extent from the present period to the period at the expiration of useful life [190]. The major job of RUL estimation is to prognosis the period left prior to the system drops below its functioning ability depending on the condition monitoring particulars. The RUL prognostics methods can be categorized into four classifications in proportion to their fundamental approaches and procedure, i.e., physics model-based techniques, statistical model-based techniques, AI techniques, and hybrid techniques [189]. Figure 9 shows the categories of RUL prediction approaches. A prognostic procedure for bearing failure and comparison of various RUL prognostic methods can be found in [191]. In general, the primary elements of the RUL prognostic procedure can be categorised into three steps- feature selection, health assessment, detection and prediction triggering [192]. Several types of sensors can be utilized for collecting data from the observed equipment. Depending on this data, the actual fitness states can be traced by selected criteria. A degradation replica is usually connected to failure time by joining historical data with the failure occurrence. To link monitoring information with RUL, Bayesian-based models are useful with the maximum likelihood estimation process to get unknown parameters [192]. The degradation process and RUL are closely related.Because most degradation processes can be reflected by vibration features, and the importance of vibration analysis is articulatedin [193]. The 1st action in RUL prediction is to analyze the decaying procedure. To process monitoring data, filtering procedures are commonly used. A conventional approach to process observing information is Kalman filtering [192], which is a numerically periodic digital processing approach for the prediction of the condition of a dynamic system [194]. An extended Kalman

TABLE 3. Comparison of various methods to estimate different states of LIB

Battery State	Methods		Benefits	Drawbacks	Reference
SOC	Model-based methods	Electrochemical model	1. Highly accurate SOC estimation 2. Ability to capture mechanism	Intensive computational efforts	[68], [162], [98]–[101]
		Equivalent circuit model	1. Simple structure 2. High extensibility	Parameter require to be adjusted	
	Data-driven methods	Artificial neural network	1. Powerful matching ability 2. Flexible	1. Potential over-filtering problems 2. Sensitive to optimization methods	
		Support vector regression			
	Direct calculation methods	Look-up tables method	Easy to be implemented	Difficult to measure the precise parameters	
		Coulomb counting method			
SOE	Adaptive algorithm-based methods	Kalman filters	1. Error self-correction 2. Noise immunity 3. Long-term reliability	1. Sensitive to environment and load 2. High computational complexity	[130], [163]–[170]
		Particle filters			
		Observers			
	Direct calculation methods	Power integration method	Easy to be implemented	1. Open-loop error accumulation 2. Sensitive to parameter inaccuracy 3. Fragile to aging 4. Large calibration work	
		Characteristics mapping method			
	Machine learning methods	Artificial neural network	1. Flexible 2. Powerful nonlinear fitting	1. Sensitive to the training method 2. Potential over and under-fitting	
SOH	Physics-based models	PDEs to describe side reactions that result in battery degradation	1. High accuracy 2. Clear meanings	1. Heavy computational load 2. Difficult model parameterization	[171]–[177]
	Empirical models	Experimental data-filtering models and specialized observers	1. Simple structure 2. Easy implementation	1. Poor robustness 2. Relative low accuracy	
	DVA/ICA-based methods	Battery high features based on DV/IC curves	Indicative of inter-calculation process	High requirement of voltage and current measurement	
	Data-driven methods	Massive data sets and AI methods such as ANN and others	No requirement of the knowledge of underlying mechanisms	1. Sensitive to quality and quantity of data 2. Potential over-fitting problems	
SOP	CMs-based methods	Static interdependence among SOP and other cell state parameters	1. Easy to be implemented 2. Straight forward characteristics	1. Hard to look at battery previous and current information 2. Amounts of information required to be kept in multi-dimensional form	[134], [178]
	Model-based methods	ECM is the main choice	1. Simple structure 2. High extensibility	1. Parameter of ECM required to be adapted 2. Hard constraints must be satisfied 3. SOP estimation based on EM is difficult	
		Particle filter, model predictive control, kalman filter, least square			
SOT	ITD-based methods	Empirical formula establishment between impedance characteristics and temperature.	Simple relationship, no thermocouples	1. Only average temperature captured 2. The requirement of high precision instruments	[132], [133], [179]–[184]
	Model-based methods	Simplified thermal models and specialized observers or estimation algorithm	1. Simple structure 2. Easy implementation	1. Poor robustness 2. Requirement of sensors 3. Be vulnerable to noise	
	Integrated methods	Combination of ITD method and filtering based on the thermal model	1. Simple structure 2. Sensor-less estimation 3. More elaborate temperature distribution	1. Requirement of high precision instruments 2.Poor robustness	
SOS	Qualitative evaluation methods	Specialized organizations assign hazard levels to confirm SOS qualitatively	1. Key implementation 2.Reference standards are available	1. Quantitative description deficient accuracy 2. Probability of existing different standards	[185]–[188]
	Quantitative calculation methods	In light of the definition of SOF, hazard models, and risk mitigation analysis, a quantitative way is taken to depict SOS	1. Quantitative description sufficient accuracy 2.The Online calculation is available	1. Lack of accurate sub-functions 2. Incremental computational complexity of concerning more battery states	

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filtering method was proposed in [195]. To set up a conditional prognostic density operation for RUL of a system part, the Kalman filtering method was merged with condition monitoring particulars. In [195], the establishment of a model for RUL prediction was also introduced.

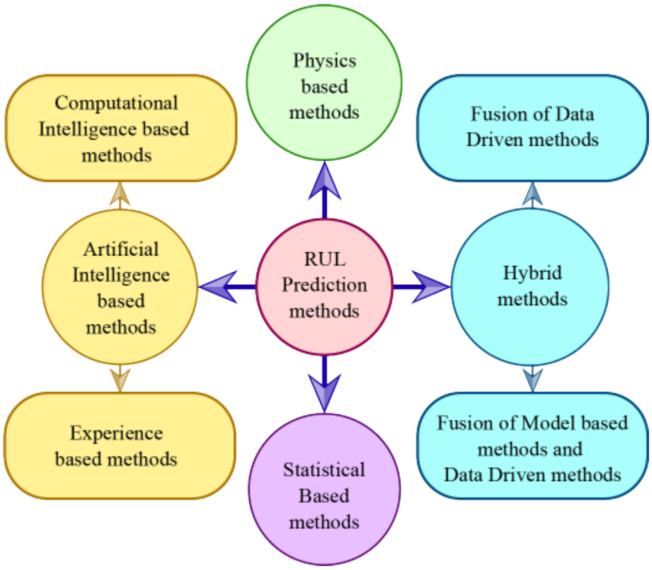

FIGURE 9. RUL prediction approaches

A. STATISTICAL MODEL-BASED APPROACHES

Statistical models predict the initial impairment and development according to the preceding observation findings on the same systems. The approach does not require data for the system aging but needs a considerable amount of the effectual data set [196]. Statistical modeling methods are widely used in RUL prediction to analyze data that has been gathered previously and for observational studies of existing data. The statistical models can describe the predictability of the degradation approach and its impact on RUL estimation. This prediction approach is the most used approach of the four approaches shown in Figure 9.

B. ARTIFICIAL INTELLIGENCE (AI) BASED APPROACHES

AI-based approaches develop the system degradation models by applying AI techniques to available observations [197] to fit the variable degradation pattern. By generalizing the parameters to the failure threshold, the RUL is determined [198].

C. PHYSICS-BASED APPROACHES

Physics-based approaches are focused on the specific chemical and physical phenomenon that impacts battery functioning and finds the details of performance evaluation [199]. Even so, this is not possible to build a perfect model for battery simulation as many components interact with each other and affect the degradation of battery function, particularly since degradation of the battery is active and non-linear.Since it is hard to observe a battery's inner conditions in real time, an exact physical model is difficult to obtain [200].

D. HYBRID APPROACHES

The hybrid approach is a combination of more than one model in order to accumulate their superiority and overcome individual restrictions to update the RUL prediction output. The hybrid approach usually has two categories: the hybridization of both data-driven plus model-dependent procedures; on top of the integration of various data-driven process [201]. A hybrid randomized learning-based ensemble data-driven SOH assessment and RUL prognosis method is suggested in [202] to accurately predict the RUL and SOH of LIBs. The extreme learning machine (ELM) and Random Vector Functional Link Neural Network RVFL are applied for hybrid learning. A health indicator is selected as featured inputs to predict the degradation trend of input. The nonlinear autoregressive (NAR) structure is designed to decrease the RUL prediction error of each learning model. Here, the RUL prediction accuracy result is provided with 99% confidence.

The Table-4 represents a comparative study of the basic advantages and disadvantages of various RUL prediction models.

V. RUL ESTIMATION METHODS FOR LIB

RUL estimation predicts the ineffective period of a battery and minimizes the danger for batteries by evaluating the cell condition [218], which is the main factor in planning proper maintenance and decreasing mishap risks [219]. RUL estimation accuracy is not always sufficient because of a lack of data availability, model complication, and system limitations. Consequently, different models are applied with various methods to predict the RUL to the most accurate level possible. Even though the aging level of a battery cannot be measured directly, the remaining battery life can be estimated, which can then be used to calculate the ageing level of battery [220]. As shown in Figure 10, RUL methodologies can be categorize into four classes: adaptive filter methods, intelligent methods, stochastic methods, and other methods [221]. These classifications are discussed later in this section.

The procedure for RUL estimation is given in Figure 11. In figure 12, a general LIB RUL estimation procedure is shown. The individual cell of a LIB reliability test data is given to a model which verifies the data to estimate the RUL. Several steps, called filtering, are performed for the data validation.

A. ADAPTIVE FILTER TECHNIQUES

In image processing, adaptive filters are generally applied to restore or enhance data by separating noise. The following are some adaptive filter techniques applied in the RUL prognosis of Li-ion cells.

1) Unscented Kalman Filter

In 2015, a method was introduced in [222] using Relevance Vector Regression (RVR) with Unscented Kalman Filter (UKF) and this was implemented to RUL prognosis with

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TABLE 4. Comparison of RUL Prediction Models

Categories	Advantages	Disadvantages	Reference
Physics-based models	1. Accurate estimation result 2. Suitable for nonlinear systems 3. Provides the details of degradation	1. Not suitable for real-life applications 2. Requires detailed knowledge of system 3.Accuracy is affected by small experiment condition changes	[203]–[206]
AI-based models	1. Suitable for nonlinear systems 2. Data models are not required 3. Simple calculation	1.A large amount of data required 2. Uncertain factors are not considered	[207]–[209]
Statistical based models	1. Support uncertainty representation 2. Suitable for nonlinear systems 3. Suitable for any kinds of the state space model	1. Greater calculation difficulties 2. Allows uncertain parameters	[210]–[213]
Hybrid models	1. Has the advantages of combined methods 2.Accuracy can be greatly improved 3. Increased effectiveness and stability	1.A large amount of calculation 2. A high level of research required	[214]–[217]

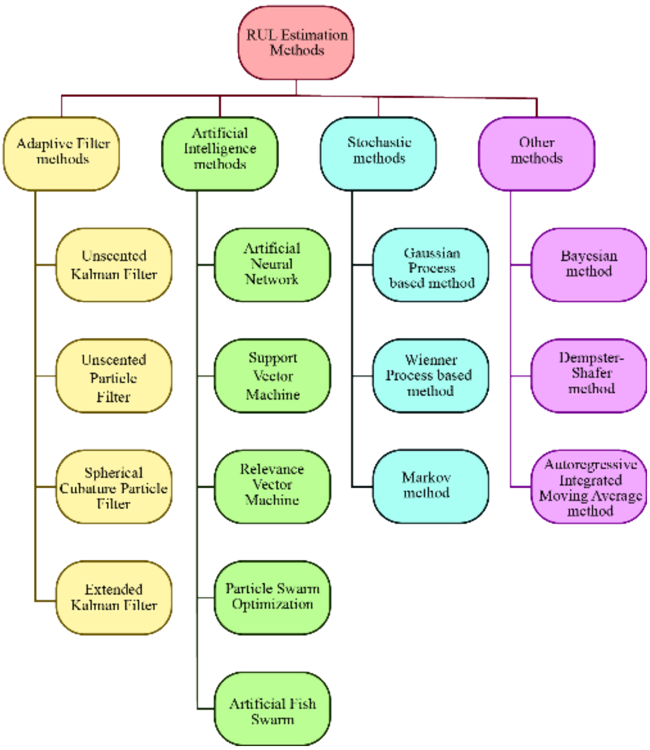

FIGURE 10. RUL Estimation Methods for LIB

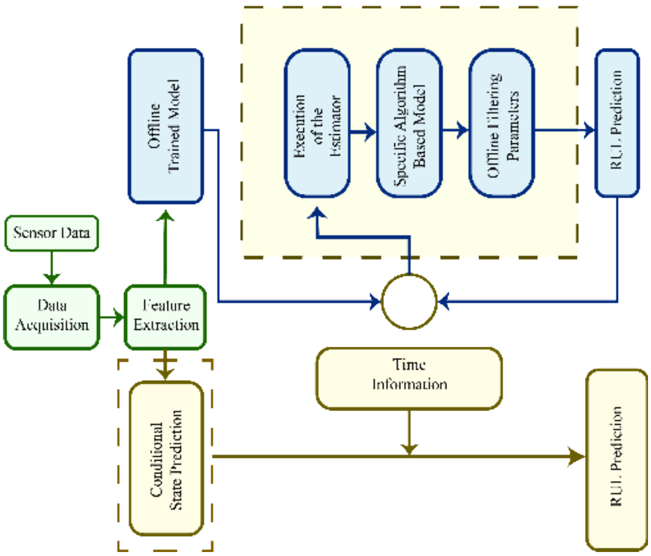

FIGURE 11. Basic RUL Prediction Procedure

short-term capacity approximation of battery cells. The suggested model promises greater accuracy and assurance than Extended Kalman Filter (EKF). Xue et al. [223] suggested a combined algorithm in 2019, which integrates genetic algorithm optimized support vector regression (GASVR) and adaptive unscented Kalman filter (AUKF) to improve the accuracy in RUL approximation for Li-ion cells. The suggested model was demonstrated to attain better approximation accuracy than available techniques such as the unscented Kalman filter, extended Kalman filter, adaptive unscented Kalman filter, adaptive extended Kalman filter (AEKF), and relevance vector regression. Again in 2019, the UKF method has been hybridized with a back propagation (BP) neural network to improve the approximation accuracy of RUL of LIBs in [224]. The BP neural network approximates the residual of UKF by auto-regressive form. The UKF uses the estimated residual to update the degradation model framework recurrently. The simulation shows that the suggested method gains far better approximation accuracy and is more adaptive to the degradation features of various approximation start points of several individual batteries. The paper describes the battery capacity attenuation equation as:

$$Q = ae^{bk} + ce^{dk} \tag{1}$$

Here, battery capacity is Q, the d, c, b, a contains noise and, k is the cycle.

2) Unscented Particle Filter

In 2013, an improved unscented particle filter (UPF) algorithm was developed to predict battery RUL [225]. The paper described the UPF algorithm and PF algorithm individually and then built a degradation model depending on the understanding of Li-ion cells. The estimation result was obtained through the UPF algorithms and degradation model. After analyzing the outcomes, it was observed that UPF predicted the actual RUL with 5 percent less error. In 2014, another

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TABLE 5. MSE of different particle filtering methods for 100 independent runs

Algorithm	MSE	
	Mean	Var
Unscented Particle Filter	0.070	0.006
Unscented Kalman Filter	0.280	0.012
Particle Filter: Generic	0.424	0.053
Extended Kalman Filter	0.374	0.015

improved UPF method was developed in [226] for analyzing the RUL of storage cells. Sigma specimens of unscented changes in conventional UPFs were produced by remarkable value decomposition. The sigma points were generated by the standard unscented Kalman filter to produce a convoluted suggesting allocation. Studies show that the performance of this method was more promising than the UPF. Zhang et al. [227] suggested an improved UPF approach dependent on linear optimizing combination re-sampling to upgrade the result exactness. It was observed that the suggested method promises greater accuracy in the RUL prognosis of LIBs, contrasted besides the available PF-dependent and UPF-dependent methodologies. A comparison of different particle filtering methods is shown in Table-5 according to their errors during 100 independent runs. A better unscented particle filter (IUPF) method was suggested in [18] for LIB RUL estimation depending on Markov chain Monte Carlo (MCMC). The method applied the MCMC to overcome the issue of specimen destitution inside the UPF process. Additionally, the IUPF method is suggested on the basis of UPF, so it can also restrain the particle degradation being in the standard PF algorithm. In 2020, [228] presented a novel hybrid method using UPF with optimized multiple kernel relevance vector machine (OMKRVM) for making up the deficiencies of single methods in LIBs RUL estimation. When the UPF-OMKRVM method is compared with the traditional methods, the test outcome ensures that it has great prediction accuracy in li-ion battery SOH and RUL estimation. A novel PF framework based on conditional variational autoencoder (CVAE) and a re-weighting strategy was proposed in [229] RUL estimation of batteries. From the test results the paper claims that the method has achieved more accurate prediction results compared with some traditional methods.

3) Spherical Cubature Particle Filter

In 2016, [230] proposed a technique to estimate the RUL of LIBs. For cell capacity, the state-space model was initially built to compute cell charge degradation. A spherical cubature particle filter (SCPF) was then applied to identify the solution to the state-space model. The study showed that the suggested model was more effective in RUL prediction than the available PF-based prediction algorithms.

The equation for spherical cubature integration and the standard PF represents the mean and variance of the transformed variable.

$$\int f(\varepsilon)\, N(\varepsilon|0,1)\, d\varepsilon \approx \frac{1}{2n}\sum_{k} f\left(\sqrt{n}u^{k}\right); k = 1,2,3....2n. \tag{2}$$

Here, ε is the multidimensional unit Gaussian distribution having a unit covariance matrix and zero mean, and u^k is the unit vector generated from a symmetric set.

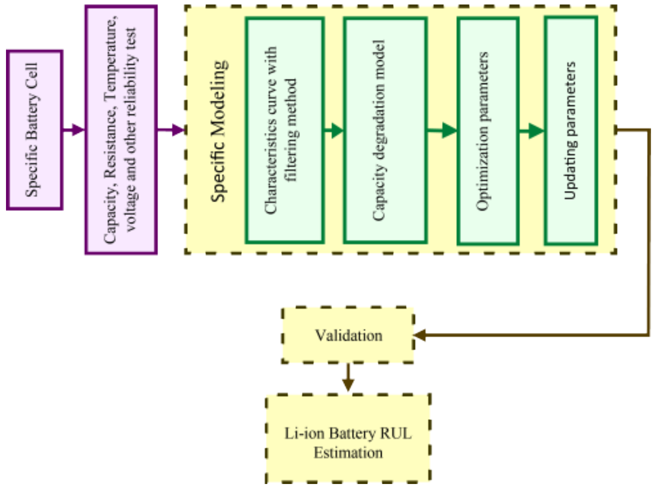

FIGURE 12. Li-ion battery RUL estimation procedure.

B. INTELLIGENT TECHNIQUES

Artificial intelligence techniques are now utilized in the procedure of inspecting data-rich and complex data in semantics as well as for modeling intelligent information models. The RUL of batteries is also estimated using various intelligent techniques. A few of the techniques are discussed in the following.

1) Artificial Neural Network (ANN)

ANN is a well-recognised machine-learning algorithm which are widely used due to their ability to discover non-linear relationships between variables [231]. [232] proposed a way of approximating the RUL of Li-ion cells depending on the long short-term memory model, empirical mode decomposition, and deep neural network (DNN). The suggested approach yielded a more exact prognostic outcome than the hybrid model of auto-regressive integrated empirical mode decomposition. Mao et al. [233] developed a Sliding Time Window (LSTM-STW), Long Short-Term Memory Network, and Sine or Gaussian function, Levenberg-Marquardt algorithm (GS-LM) hybridization battery cells RUL estimation process depending on ensemble empirical mode decomposition (EEMD) in 2020 to calculate inaccuracy in RUL prognosis. The outcome showed that the method promises high accuracy predictions. The suggested process was more efficient than any other battery RUL prediction process. Qu et al. [234] presented a neural network-dependent method in 2019, which hybridize particle swarm optimization accompanied by long short-term memory (LSTM) network with an

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attention procedure for RUL prognosis and SOH observation of the LIBs. A data set of Lithium-ion cells offered by NASA was applied to judge the suggested method and the test showed that the proposed process has greater accuracy than the traditional process. In 2018, [218] investigated a deep-learning-enabled battery RUL estimation. The LSTM recurrent neural network (RNN) was engaged to study the long-term reliances amid the degraded capacities of Li-ion cells. The established process was able to approximate the RUL of cells and does not require any offline training data. If any offline data is available, the RUL can be estimated faster than in conventional processes. Earlier in 2016, the relation between the charge curve and RUL was produced by the feed-forward neural network (FFNN) because of its clarity and efficiency [235]. However, the FFNN with importance sampling was shown to be an accurate prediction method for RUL estimation. A multi-factor optimization process for RUL prediction of LIBs is proposed using a novel data driven process. The method applies the technique for order preference by similarity to ideal solution (TOPSIS) method. This process is dependent on improved particle swarm optimization (PSO), information entropy, and moving average filter (MAF) for multi-parameter optimization. This method gives a great estimation accuracy under the both low and high temperature condition and use less training data [236]. A prediction-based test optimization method was shown in [237] for decreasing cycle test with estimated lifespan for Li-ion batteries. A hybrid transfer-learning method automatically selects historical test data and trained model of other formulations to help construct models of the target batteries. It can improve prediction accuracy despite short-term test data containing insufficient global degradation information. A new RUL prediction process dependent on LSTM was proposed in [238] to predict RUL in the comportment of capacity regeneration phenomenon. Multiple measurable data from BMS such as temperature charging profiles, voltage, and current were accounted for whose forms is changed by aging. In contrast to the conventional LSTM method which equalizes output section accompanied by input section like one-to-one configuration, the paper supports many-to-one configuration to be adaptable towards different input categories along with considerably decrease the amount of variables for finer generalization. In 2020, Auto-CNNLSTM method for RUL estimation was suggested in [239]. The model is developed depending on deep convolution neural network (CNN) and LSTM to mine deeper information in finite data. An auto encoder utilizes to augment the dimensions of data for increased effectiveness in the training of CNN and LSTM.

The Figure 13 represents the output as a outcome of the transmission of given data through layers and neurons. This is a sort of distributed representation. Single artificial neuron has the meaning of local representation. As a result of transformation across layers and neurons, the entire network has a meaning of distributed representation.In a training process, ANN models are regulated to limit the fault within the actual output and the model outputs. This is dependent on the training data set including the outputs of the set of corresponding input vectors. The performance function can be expressed as:

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(y_k - d_k)^2 \tag{3}$$

where N represents the amount of training output and input pairs, d_k the actual output, and y_k the model output.

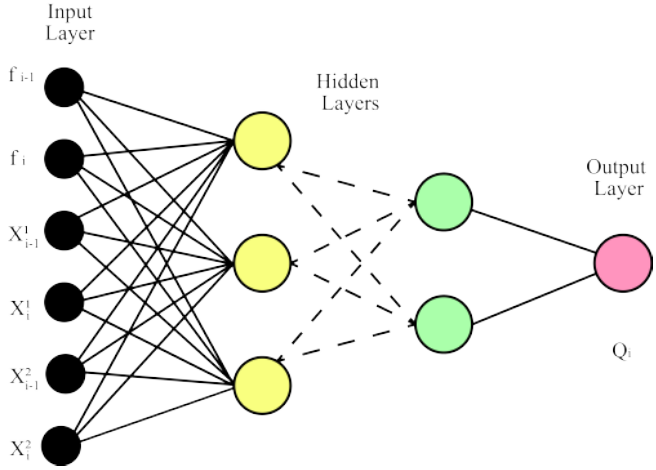

FIGURE 13. The artificial neural network structure for RUL prediction.

2) Support Vector Machine

In 2019, a process for RUL prediction of Li-ion cells which employed a support vector regression (SVR) and an artificial bee colony (ABC) was suggested to better the estimation result [242]. A simulation with test data was run with the help of NASA Ames Prognostics Center of Battery Excellence data sets to validate the suggested process. Results showed that framework enhancement with the ABC algorithm was robust compared to that with the PSO process. Moreover, the ABC-SVR process has greater accuracy than PSO-SVR as well as over and above available processes. Again in 2019, a perfect partial discharge data (PDD)-dependent SVM process was suggested through to RUL estimation [241]. This suggested method performed the task of extracting the critical characteristics from the electromotive force and thermal change of PDD for instructing the SVM method which was then used to predict RUL. In electric vehicles, this process can be used for online RUL prediction. A perfect SVR dependent cell SOH state-space method was built for cell RUL prognosis and SOH assessment was proposed in [254]. The results showed that the suggested SOH approximation method had an exact and robust outcome. The paper used the following equations to create a state space method to predict cell degradation factor:

$$\lambda_R(i) = \lambda_R(i-1) + w_1(i) \tag{4}$$

$$x_R(i) = x_R(i-1)exp(\lambda_R(i-1).\Delta i) + w_2(i) \tag{5}$$

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TABLE 6. Comparison studies of various RUL prediction methods

Technique	Method	Test Condition	Result/Accuracy	Publication Year	Reference
Adaptive Filter	UPF-OMKRVM	70 cycles	RMSE 0.0051 and MAPE 0.2592	2020	[228]
	AUKF-GASVR	60 cycles	RMSE 0.0134 and MAE 0.0091	2019	[223]
	UKF-BP	172 cycles	RMSE 0.0078 and MAE 0.0070	2019	[224]
	U-LOCR-PF	70 cycles	Relative prediction error 1% RMSE 0.01983	2018	[227]
	IUPF	30 cycles	Estimated Error 0% and RMSE Mean 0.001102	2017	[240]
	SCPF	90% of AL	Absolute error 14	2016	[230]
	UKF	100 cycles	RMSE 0.01156 and MAPE 0.1611	2015	[222]
	UPF	32 cycles	RMSE 0.00250 and Estimated error 2.04%	2013	[225]
Intelligent Technique	EMD-DNN-LSTM	130 cycles	RMSE 0.0021	2020	[232]
	EEMD	-	MAPE 0.0244 and RMSE 0.0232	2020	[233]
	MC-LSTM	-	RMSE 0.0168 and MAPE 0.0105	2020	[238]
	Auto CNN-LSTM	Output encoder size 50	RMSE 0.0503 and Accuracy 94.97%	2020	[239]
	PA-LSTM	90 cycles	RMSE 0.0166	2019	[234]
	PDD-SVM	-	Accuracy 94% and RMSE 0.003108	2019	[241]
	ABC-SVR	84 cycles	MAE 0.0072 and RMSE 0.0139	2019	[242]
	RVM-GM	100 cycles	RMSE 0.00960422	2019	[243]
	LSTM RNN	354	Standard Deviation 11	2018	[218]
	ADNN	20 cycles	RMSE 0.0666 and Accuracy 93.34%	2018	[244]
	DBN-RVM	-	MAE 0.107106 and RMSE 0.012754	2017	[245]
	IP-RVM	40 cycles	RMSE 0.0173	2015	[246]
	SVM	-	RMSE 0.1659	2015	[247]
	AFS	300 cycles	RMSE 0.0836	2013	[248]
Stochastic Technique	IHIs-GPR	-	MAPE 0.0565 and RMSE 0.0005	2020	[249]
	GPM	60 cycles	RMSE 0.0158	2016	[250]
	WPME	68 cycles	Mean square error 0.001	2014	[251]
Others	EMD-ARIMA	60 cycles	RMSE 0.0209	2016	[252]
	Naive Bayes	16.1 cycles	RMSE 0.17	2014	[253]

$$R(i) = x_R(i) + v(i) \tag{6}$$

Where i represents the cycle number, $\lambda_R(i)$ is degradation factor at cycle amount, smoothed impedance value is x(R), and $w_1(i)$, $w_2(i)$, and v(i) is output noises and system.

The first two equations are considered as state equations, and the equation number three is output equation.

A novel method was suggested for RUL prediction of LIB in [247] which combined regression and classification of support vector machine. The process for RUL prediction was established dependent on the critical characteristics using SVM. In 2014, [255] used the Support Vector Regression-Particle Filter (SVR-PF) to predict RUL of batteries.The suggested RUL prediction method obtained better outcomes and the SVR-PF had better prognostic capability whan compared with the good quality particle filter (PF) method.

3) Relevance Vector Machine

By applying the gray model (GM) and the relevance vector machine (RVM) alternately, [243] estimated battery RUL and SOH. The RVM and GM corrected each other's prognostic outcomes continuously, which helped in reducing the final prediction error. Test outcomes along the NASA data set showed that the suggested process might exactly build the degradation model and obtain a finer outcome for RUL prediction when contrasted with using only RVM or only the GM process. Liu et al. [246] in 2015, implemented an online training model in the RVM algorithm to improve the estimation result and introduced an increasing enriched RVM algorithm to the model with the help of a well-organized on-line training process. The suggested online training method achieved an enriched prognostic result and also improved the operating efficiency for battery RUL prediction. In 2017, an RUL prognosis process dependent on the Relevance Vector Machine (RVM) and Deep Belief Network (DBN) was suggested in [245]. This hybrid approach used DBN to extract characteristics from the capacity decadence of LIBs and RVM to utilize the retrieved characteristics to estimate RUL from the CALCE cell data sets. Weng and Feng [92] extracted a novel health indicator (HI) from the battery current profiles that can be directly measured online. Furthermore, the indicator is optimized by Box-Cox transformation. This was evaluated by correlation investigation for degradation modeling accurately.The RVM formula is used to make a

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prognosis for battery RUL based on the extracted HI.

For a considered data set the outcome of a regression formula is given by:

$$t = y\left(x\right) + \varepsilon \tag{7}$$

where N is the data sample number, nonlinear function is y(x), and noise term subject is ε which is independent additive .

4) Deep Neural Network

Lei Ren et al. [256], proposed a deep learning approach integrating with autoencoder (Alternating Deep Neural Network-ADNN) for multiple lithium-ion battery RUL predictions. To constitute battery health degradation, the authors proposed 21- dimensional feature extraction method accompanying the autoencoder model. The method was applied to a dataset provided by NASA. Using deep neural networks (DNN) data-driven model was presented to estimate both SOH and RUL of LIBs [257]. The result of the work was tested in the LIB dataset provided by the NASA Ames Prognostics Center of Excellence (PCoE). This result was also contrasted with various ML-based formula results. However, their model was in the preliminary stage and only used a deep neural network to build the deep learning model. Fractional Brownian Motion (FBM) which is a non-Markovian method, was suggested to prognosis the RUL of Li-ion cells [258]. The parameters of the model were predicted applying maximum likelihood prediction. The Hurst exponent was estimated using the fly optimization algorithm. Chen, Liaogehao, et al. [259] investigated the RUL prediction of LIBs using hybrid data-driven method employment based on error compensation (EC) and Support vector regression (SVR). They implemented the idea of EC by combining the predictions of RUL prediction with phase-space reconstruction SVR (PSR-SVR) and forecast error. The key parameters were utilized with a generic algorithm (GA) for better accuracy. They also verified the effectiveness of their work using a dataset of LIBs provided by NASA. Zhang, Yunwei, et al. [260], showed that the gaussian process regression (GPR) can predict the RUL and estimate the capacity of LIBs utilizing electrochemical impedance spectroscopy (EIS). They generated the largest dataset totaling over 20,000 EIS spectra with a wide range of frequencies at various states of capacity and temperature. The model was more accurate than conventional methods.

C. STOCHASTIC TECHNIQUES

1) Gaussian

In 2020, short-term SOH estimation was completed by adding the Gaussian process regression (GPR) approach with probability prognostics [249]. The SOH value along with three Indirect Health Indicators (IHI) was applied to forecast the RUL of Li-ion cells using the GPR method. Earlier in 2019, a perfect process combined secondary health indicator (HI) and many Gaussian process regression (GPR) processes to predict RUL for batteries [261]. The HIs were used to extract features in the constant-voltage and constant-current changing method and the GPR model was utilized alongside the merged kernel functions for better prediction of capacity regeneration. The estimated capacity was used to contrast with the threshold to achieve the RUL estimation outcome.

2) Wienner

Tang et al. [251] suggested a perfect RUL prognosis approach for Li-ion cells depending upon Wiener process alongside measurement error (WPME). The truncated normal distribution (TND) dependent modeling method for the predicted degradation level was used to gain a closed-form and accurate RUL distribution by considering the allocation of the predicted drift factor and the measurement uncertainty. The maximum likelihood estimation (MLE) approach for population dependent parameter prediction was used for the better RUL estimation accuracy. The model is stated by:

$$Y(t) = X(t) + \varepsilon = \lambda t + \sigma_B B(t) + \varepsilon \tag{8}$$

Here, Y(t) is the degradation phase containing the measurement error, X(t) the is degradation step absent of measurement error, λ represents drift parameters, ε is the measurement error, $\sigma_B(t)$ is the diffusion factors, and standard Brownian motion is expressed as B(t).

D. OTHER TECHNIQUES

1) ARIMA

ARIMA or autoregressive integrated moving average models are loaded with time series data for estimating future points in the series or to characterize the data better than ARMA [262]. In 2016, a perfect method that combined the autoregressive integrated moving average (ARIMA) model and empirical mode decomposition (EMD) was suggested in [252] for the RUL prognosis of Li-ion cells. First, EMD and then the ARIMA model was applied to estimate the capacity regeneration and global deterioration trend. This prediction was used to achieve a SOH estimation from which the RUL was predicted. This model performed better and achieved more accurate results than monotonic echo sate networks, relevance vector machines, and ARIMA-only models. The ARIMA model general form is expressed as:

$$\phi\left(B\right).\left(1-B\right)^{d}.x\left(t\right) = \theta\left(B\right).\varepsilon\left(t\right) \tag{9}$$

here, $\varepsilon\left(t\right)$ is the arbitrary error series which is imagined to be a white noise containing an equal variance and zero mean, backward shift operator is B, $x\left(t\right)$ is the SOH series, and d is the order of the distinct computation operator respectively.

2) Bayesian

A naive Bayes (NB) based method was suggested for the cell degradation approach to estimate RUL considering various current rates and ambient temperatures [253]. When in constant discharge environments, the RUL can be estimated with the NB approach without the accurate values of the functioning parameters. Comparative Studies between various methods show that the prognosis results outperformed SVM in

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terms of robustness and accuracy.A probabilistic method for battery degradation modelling and health prognosis based on the features extracted from the charging process is presented using the dynamic Bayesian network in [263].

The Bayesian learning for a new recognized data sample, can be denoted as:

$$p\left(t_{N+1|t}\right)=\int\int\int p\left(t_{N+1|w,\alpha,\sigma^2}\right)p\left(w,\alpha,\sigma^2|t\right)dwd\alpha d\sigma^2 \tag{10}$$

where, α is a vector of N + 1 hyper-parameters, w is the corresponding weight vector, and σ^2 is variance.

E. EVALUATION MATRICES

Some traditional matrices are applied to evaluate and assess the estimation performance and accuracy of a model. Examples include RMSE, ERMSE, mean absolute percentage error, EMAPE, mean absolute error, EMAE, prediction error, ERUL, and relative error ERA are used to indicate the performance and accuracy of RUL estimation [223]. The equation form of these matrices can be denoted as:

$$E_{RMSE}=\sqrt{\frac{1}{n}\sum_{k=1}^{n}(y_k-\hat{y}_k)^2} \tag{11}$$

$$E_{MAE}=\frac{1}{n}\sum_{k=1}^{n}\left|\frac{(\hat{y}_k-y_k)}{y_k}\right| \tag{12}$$

$$E_{MAPE}=\frac{100\%}{n}\sum_{k=1}^{n}\left|\frac{(\hat{y}_k-y_k)}{y_k}\right| \tag{13}$$

$$R^2=1-\frac{\sum_{k=1}^{n}(y_k-\hat{y}_k)^2}{\sum_{k=1}^{n}(y_k-\bar{y}_k)^2} \tag{14}$$

$$E_{RUL}=\left|R_t-R_p\right| \tag{15}$$

$$E_{RA}=1-\left|\frac{R_t-R_p}{R_t}\right| \tag{16}$$

Here y_k indicates the actual battery capacity, $\hat{y}_k$ indicates predicted battery capacity, R_t is the true RUL result,and R_p describes the RUL prediction value.

For the E_{RMSE}, E_{MAE} and E_{RUL} indicators, the closer the value gets to 0, the higher is the prediction accuracy. And for R^2 and E_{RA}, when the value is close to 1, the prediction result is more accurate.

VI. DISCUSSION AND SCOPE FOR FUTURE WORK

The main goal of this review is to review various battery RUL prediction approaches and battery management systems, and to provide sufficient information about commercially or publicly available battery data sets. Initially, a overview of the LIB data acquisition system was provide; figure 2 will help understand the overall data acquisition and RUL estimation process. In section 2, various commercially and publicly available battery data information was given, from which the required information about the data set of batteries may be extracted. Table 1 provides various information about those data sets. A brief discussion about battery management can be found in section 3. The process of generating a battery data set was generalized for both simulating and experimental data sets using a data acquisition card. Various RUL prediction methods with related terms and mathematical modelling are given in section 4. Different RUL prediction approaches considering LIB RUL estimation, is discussed in section 5. Table 2 compares different RUL prognostics techniques. The main goal of this review was to give a comprehensive overview of data acquisition and RUL prognostics of Li-ion batteries. Miscellaneous RUL prediction methods are classified into a statistically-based model, hybrid model, Artificial intelligence-based model, and physics-based model and compared with advantages, limitations, and applications from several research papers. Many RUL prediction methods are not yet applied to prognosis the RUL of LIBs. Consequently, there is considerable future work scopes:

1) A fusion of data-driven methods along with other methods may achieve more reliable RUL prognostics for Li-ion cells.
2) The more reliable data source may be obtained to gain high accuracy in RUL estimation.
3) Advance battery management can be investigated using multi-state joint estimation of various states (SOC, SOE, SOP, SOH, SOP, SOT, SOS).
4) Battery management future research trends could consider the use of artificial intelligence, big data, and machine learning algorithms.

The literature review shows that hybrid RUL estimation methods have gained better accuracy and less errors in the estimation process. Fusion of various estimation methods can further develop the accuracy and play a role in the providing better RUL estimation.

VII. CONCLUSION

The battery is the power source for many consumer electronics, mobile phones, laptop computers, electric vehicles, spacesuits, submarines, rovers, and other devices that require with stored power. Research in this area is attracting greater attention from scientists, engineers, and researchers. The review was conducted on the detailed aspects of battery functioning, data sets, battery management, and RUL prediction approaches. The most notable parts of this review are:

1) Battery data acquisition and available datasets: Data is the most vital and basic element in carrying out any research and there are very little good information available for commercially and freely available data sets of batteries. None-the-less, this review has detailed those battery data sets that are available publicly and commercially, to assist researchers searching for suitable battery data sets. A process of generating simulation-based and experimental data sets can be found in figure 2. Moreover, in table 1, a comparison of various data sets is also given which also includes data category, format, and other parameters information.

2) Battery Management System and future research trends: The development of a proper battery management system is a research topic currently attracting considerable attention. In this part of the review, many battery management terminologies with related research work were reviewed. A basic battery management system concept was illustrated in figure 6, and future research trends were discussed.
3) RUL prediction approaches and comparison among various RUL prediction techniques with over 150 research reviews: Considering the importance of RUL prediction of battery and other systems, many RUL prediction techniques were reviewed including future research directions. Table 6 provides a comparison of RUL prediction techniques with their operating condition and accuracy.
4) Battery RUL prediction algorithm review: RUL estimation techniques used for battery RUL estimation were reviewed, including techniques such as: adaptive filter techniques, intelligent techniques, stochastic techniques, and other techniques.

RUL prediction is one of the prime concerns in the BMS. This paper summarizes the important RUL prediction methods and available data sets of LIB. RUL prediction approaches and algorithms for LIB are reviewed. Some online and offline available data sets for battery RUL prediction are described in the data acquisition section. A quantitative comparison of RUL prediction methods is provided to better understand the processes and the prediction results. The progress and successes during the last decade of various RUL prediction methods and algorithms are discussed in the RUL estimation methods section. Still, there are many types of research ongoing to improve the battery management system. However, various uncertain factors create a major impact on the accuracy of the RUL prognostics and uncertainty has become a critical concern in the LIB RUL prognostic research. Further research is required in this field.

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