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TOPICAL REVIEW

Review on Li-ion Battery Parameter Extraction Methods

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ABSTRACT Electric batteries have gained attention with recent developments in the transport sector, especially with electric vehicles (EVs) technology and with the rapid development in the energy storage sector with application to the electricity grid. Lithium-ion batteries (LIBs) are particularly popular due to their high-power density, high energy density, low self-discharge rate, and performance. LIB systems are also widely utilized in extreme operating conditions and harsh environments, and the safe operation of any battery management system requires rapid detection and accurate diagnosis of faults. To have an effective fault diagnosis, the nonlinear behavior of battery systems has been studied in considering the battery real-time operation. In addition, accurate battery models are used to mimic battery physical processes and predict aging. The knowledge of battery model parameters plays a crucial role in accurately predicting performance and ageing. This paper critically reviews different battery models, such as electrochemical models, equivalent circuit models, and data-driven models. Then, the parameter extraction methods for the electrochemical model were discussed critically since it has been identified as the most promising battery model and also the techniques for the other battery models may rely on these approaches as they can be derived based on the electrochemical model parameters. According to the literature parameter estimation for electrochemical models was discussed under the categories of online, offline, and analytical methods. By the state-of-the-art review conducted, it has been identified that the mixed method that combines the online and offline methods shows good performance compared to using them separately. This paper also discusses some future research directions to obtain better parameter extraction methods for electrochemical models to facilitate battery fault diagnosis.

INDEX TERMS Battery modeling, lithium-ion battery, parameter extraction, battery management systems, electric vehicles.

I. INTRODUCTION

The need for energy storage has seen significant growth due to the rapid development in electric vehicles, wider penetration of renewable energy, and smart grid technologies in addition to other applications such as hybrid electric aircraft and marine vessels. Technological advances in lithium-ion batteries (LIBs) have resulted in their adoption as one of the key energy storage devices. Advantages of LIBs over other types of energy storage devices include high energy-to-weight ratio, minimal memory effects, low self-discharge rates, and low cost [1], [2], [3]. The use of LIBs in modern applications requires a battery management system (BMS) [4], where charging/discharging, monitoring, and control of the battery state are performed to ensure safety, reliability, and optimal performance. Advanced BMS technologies [4], [5], [6] typically consist of sensors that measure the voltage, current and temperature of the battery as well as a microprocessor that processes the sensor data for fault detection and fault prognosis. To maintain the longevity

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of the battery and avoid catastrophic failure during a fault, the BMS may also have protection features such as over-charging and over-discharging protection. The development of advanced BMS technologies requires modeling of the LIB system and the LIB cell. LIB cells exhibit nonlinear behavior in multi-spatial levels and therefore the model of the LIB system is complex. A LIB system may also consist of an array of cells, and the inconsistency between the cells also poses a challenge in modeling the LIB. Mathematical models of LIBs are widely used to date and can be categorized as;

1) Electrochemical models [7], [8], [9], [10], [11], [12], [13], [14], [15], [16]
2) Equivalent circuit models [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27]
3) Data-driven models [28], [29], [30], [31], [32], [33], [34]

The quantitative linkage between the electrochemical model and the equivalent circuit models (ECM) has become a research focus in the recent past [35], [36], [37]. Since the ECM has an issue with the limited applicability for long-term battery performance prediction under the ever-changing system dynamics [23]. Though the ECMs are preferable in real-time implementation considering the model simplicity it has the issue with lower accuracy in the low SoC level. Therefore, combining the electrochemical processes with the ECM has been discussed in the literature. It has been identified that in the physics-based ECMs, the simplification of the electrochemical model was used to address this issue [37], [38], [39]. In [37] an electrochemical model was used as the virtual battery to replicate the degradation mechanism and this simulation has been used to estimate the ECM parameters by varying the associated electrochemical model parameters. Similarly in [39] the same electrochemical model was simplified using finite volume methods and then ECM was obtained for the same. It is clear that the identification and estimation of the parameters of a electrochemical model have a much impact on developing the ECM model for real-time implementations rather than estimating the parameters for ECM using an experimental approach. Therefore, in this paper, we mainly discuss the parameter estimation method for electrochemical battery models for LIBs.

In section II a review of the construction of LIB is presented and followed by battery modeling techniques, and parameter extraction methods for electrochemical battery models in sections III, IV respectively. In section V the challenges and future directions for LIB battery model parameter extraction have been discussed and then in section V the conclusion is presented.

II. REVIEW ON THE CONSTRUCTION OF THE LIB

LIB has two distinct compounds: cathode and anode within the battery. These compounds are capable of reversibly intercalating and de-intercalating lithium ions. By convention, the anode is referred to as the negative electrode and the cathode as the positive electrode. The anode of LIB contains carbon-doped materials and the cathode contains lithium-ion

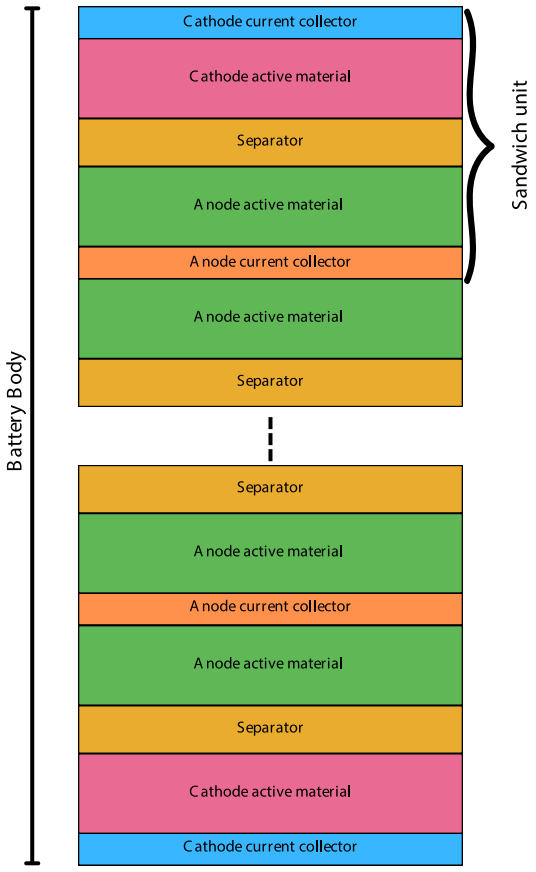

FIGURE 1. Microscopic structure of LIB [42].

intercalation compounds such as $LiCoO_2$ and $LiFePO_4$. The separator, which is placed in between the anode and the cathode, is usually a microporous polymer membrane that allows only the lithium ions to exchange between the cathode and anode and prohibits the electrons to pass through. The conventional commercial LIB separators are polyolefin membranes made from polyethylene (PE) or polypropylene (PP). They are typically designed to be less than 25 μm in thickness and have porosity around 40% [40].

The electrodes of LIB are partially submerged in a solution referred to as an electrolyte. The primary purpose of this solution is to allow ions to flow between electrodes when the battery is charging or discharging. Typically, the electrolyte in LIB is found in either liquid form, solid form, or molten salt [41]. The microscopic structure of a LIB can be considered to be a sandwiched structure where several layers are stacked and each layer consists of five parts such as positive and negative active material, positive and negative current collectors, and the separator as shown in Fig. 1 [42].

III. BATTERY MODELING TECHNIQUES

A. ELECTROCHEMICAL MODELS

Electrochemical modeling techniques [7], [8], [9], [10], [11], [12], [13], [14], [15], [16] are widely used to mathematically

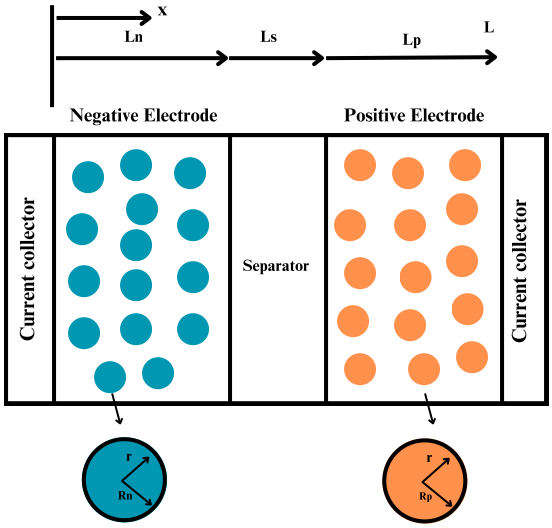

FIGURE 2. P2D Model schematic diagram.

represent LIBs and are considered to be a mature methodology among different battery modeling techniques available to date. The electrochemical model describes the electrochemical reactions occurring at the anode and cathode and the transport of ions and electrons through the electrodes and electrolyte. These models can reflect the changes of various parameters within the battery and it has been extensively used in various applications such as battery design [43], battery performance optimization [11], [13], [44], [45], battery management [46], [47], [48], battery aging modeling [49], [50], [51], [52], [53] in addition to battery fault prognosis [54], [55], [56] and fault diagnosis [57], [58], [59]. These electrochemical models can be categorized as pseudo-two-dimensional models (P2D), single particle models (SP), and modified P2D or modified SP models [14], [50].

1) PSEUDO-TWO-DIMENSIONAL MODELS (P2D) MODELING ON LIBs

The P2D model for LIBs was first reported in 1993 based on porous electrode theory and concentrated solution theory [7]. The P2D model is mainly used for the analysis and optimization of battery performance. The application of these models in real-time control and monitoring has not been widely reported due to the computational complexity of the model. The model requires solving a set of partial differential equations (PDEs) that describe the transport of lithium ions within the electrodes as well as the electrochemical reactions that take place at the electrodes-electrolyte interface.

In the P2D model, the electrodes are treated as a superposition of two continua, namely the electrolytic phase and the solid matrix. The solid matrix is modeled as microscopic spherical particles, where lithium ions diffuse and react at the surface of the spheres [14]. It is assumed that the chemical reactions occur only in the x-direction, as shown in Fig. 2, where reactions along y and z are assumed to be negligible. The diffusion of the lithium ions is assumed to react at the surface of spherical particles and defuse in the r-direction. The P2D model considers the reactions in two dimensions [60] and hence referred to as a 2D model.

The battery-charging process can be represented by the insertion of lithium ions from the electrolyte at the center of the cell to the surface of the anode. A 'particle oxidation charge-transfer reaction occurs on the surface of the anode, which is usually made of graphite. Lithium ions are introduced into the graphite lattice during this reaction making the material positively charged and enabling energy storage. The reaction can be described as follows [61];

$$C_6 + xLi^+ + x^{e^-} \rightleftharpoons LixC_6 \tag{1}$$

where C_6, Li^+, and e^-represents the graphite particle, lithium ion, and electron respectively. The value 'x' represents the number of lithium ions and electrons involved in the reaction. Lithium ions from the electrolyte are drawn to the anode during charging and incorporated into the graphite structure resulting in the transfer of electrons from the anode to the cathode. The positively charged graphite particles fill the gap left by the electron shortfall. The reverse process occurs during the discharging process where lithium ions are extracted from the anode and transported to the cathode. This lithium ion diffusion in the solid phase is represented by Fick's second law [14];

$$\frac{\partial c_s}{\partial t} = \frac{1}{r^2}\frac{\partial}{\partial r}\left(D_s r^2 \frac{\partial c_s}{\partial t}\right) \tag{2}$$

where c_s is the lithium-ion concentration in the solid phase and D_s is the diffusivity of the solid phase.

During the charging process, lithium ions are removed from the cathode and transferred to the anode by diffusion in the electrolyte phase following insertion into the crystal structure of the anode material. The lithium ions are removed from the anode during discharging process and moved by diffusion via the electrolyte phase to the cathode where they interact with the cathode substance to generate energy. Lithium ions diffusion in the electrolyte phase is modeled by Fick's second law [14];

$$\epsilon_e\left(\frac{\partial c_e}{\partial t}\right) = \frac{\partial}{\partial x}\left(D_e^{eff}\frac{\partial c_e}{\partial t}\right) + a(1 - t_+^0)j \tag{3}$$

where ϵ_e is the volume fraction of the electrolyte, c_e represents the lithium-ion concentration in the electrolyte, D_e^{eff} is the effective value of diffusivity of the electrolyte and a,t_+^0, and j represent the specific surface area of the electrode, transference number, and lithium-ion pore wall flux respectively.

During the charging process, electric charge is transferred from the power source to the battery, and during the discharging process, the charge is transferred from the battery to the load. The total amount of charge within the battery must remain constant during this process according to the principle of the conservation of charge. This charge conservation in the solid phase is modeled by Ohm's law [14];

$$\frac{\partial}{\partial x}\left(\sigma_s^{eff}\frac{\partial \phi_s}{\partial x}\right) = Faj \tag{4}$$

where σ_s^{eff} is the effective value of solid phase conductivity, ϕ_s represents potential of solid phase and F indicate the Faraday constant. Similarly, the charge conservation in the electrolyte phase is modeled by [14];

$$\frac{\partial}{\partial x}\left(\kappa_e^{eff}\frac{\partial \phi_e}{\partial x}\right)+\frac{\partial}{\partial x}\left(\kappa_D^{eff}\frac{\partial lnC_e}{\partial x}\right)=-Faj \tag{5}$$

where κ_e^{eff} and κ_D^{eff} represent the effective values of electrolyte conductivity and electrolyte diffusion conductivity, and ϕ_e represents the potential of electrolyte.

During the charging process, the insertion of the lithium ions into the crystal structure of the anode material is a reduction reaction, as the lithium ions are accepting electrons from the anode material and become oxidized in the process. During discharging, the opposite occurs where lithium ions are extracted from the anode material and is an oxidation reaction, as the lithium ions are donating electrons to the cathode material which becomes reduced in the process. The charge transfer reaction is modeled using the Butler-Volmer equation, which is a two-step reaction mechanism that describes the rates of electron transfer between the electrode and the electrolyte. The equation considers the activation energy for the reaction, the exchange current density, and the overpotential, which is the difference between the actual voltage of the battery and its thermodynamic equilibrium voltage given by [14];

$$j=i_o\left(exp\left(\frac{\alpha_a F}{RT}\eta_{ct}\right)-exp\left(\frac{\alpha_c F}{RT}\eta_{ct}\right)\right) \tag{6}$$

The parameters R and T are the universal gas constant and cell temperature respectively, and the variable η_{ct} represents the charge transfer overpotential. The exchange current density i_o is given by [14];

$$i_0=kc_e^{\alpha}(c_s^{max}-c_s^{surf})^{\alpha}c_s^{surf} \tag{7}$$

The superscripts *max* and *surf* represent the maximum and surface values where *e* and *s* subscripts denote electrolyte and solid phase.

The list of parameters required to implement the P2D model [62] are listed in Table 1.

The P2D model prediction has been used as a benchmark model when the experimental data are not available [63]. In certain studies, the P2D model has been coupled with thermal models and aging or capacity fade models to reflect the ideal behavior of internal physical processes [64], [65], and therefore it can be considered a valuable tool for advanced BMS applications. for example, the authors of [64] propose a fast charging protocol optimization mechanism based on a P2D-thermal-capacity fade coupled model and dynamic program optimization. This method has minimized the capacity fade due to the solid-electrolyte interphase (SEI) increase to maximize the SEI potential to decrease the lithium plating, and to reduce the temperature rise to avoid a thermal runaway situation. In [65] a novel thermal-electrochemical model was proposed which can be applied to large-size prismatic batteries which improve the rate of BMS control-oriented programming and lessen the computational burden on onboard applications. P2D models also have been used in the state of health (SoH) estimation considering battery degradation [16], [56], [66]. In most of these methods, a simplified version of the P2D model was used for SoH estimation while coupling it with other models such as thermal, aging, and degradation models.

TABLE 1. Full set of parameters of P2D model.

Parameter Symbol	Domain	Description
σ_s	n,p	Solid-phase conductivity [S/m]
L	n,p,s	Electrode thickness [m]
κ_D	n,p	Electrolyte diffusion conductivity [S/m]
κ_e	n,p,s	Electrolyte conductivity [S/m]
$D_{e/s}$	n,p	Diffusivity of electrolyte or solid phase [m^2/s]
$\epsilon_{e/s}$	n,p,s	Volume fraction of electrolyte or solid phase
c		lithium-ion concentration [mol/m^3]
α		Anodic/cathodic charge transfer coefficient
β		Electrolyte activity coefficient
R_s	n,p	Radius of solid particles [m]
Q_p^0,Q_p^1,Q_n^0,Q_n^1	n,p	Solid phase stoichiometric number
c_s^{max}	n,p	Maximum lithium-ion concentration in solid phase
c_e^0		Initial electrolyte concentration [mol/m^3]
t_+^0		Electrolyte transference number
k		Charge-transfer constant [A $m^{2.5}$/$mol^{1.5}$]

2) SINGLE PARTICLE (SP) MODEL OF LIBs

To reduce the mathematical complexity of the P2D model, certain applications use a Single Particle (SP) model of LIBs for SoC estimation [29], [67], [68], SOH estimation [51], [69], voltage prediction [50], temperature prediction [29]. The SP model considers the entire electrode as one active particle which reduces the complex partial differential equations to ordinary differential equations to be determined and therefore increases the computational speed. The electrolyte is assumed to be infinitely conductive in or in certain instances, the electrolyte concentration is considered to be constant and the current in the electrolyte is not varying with the space [70], [71]. It is also reported that with rapidly varying currents, the SPM error will increase as the electrolyte concentration changes rapidly whereas in SPM, concentration polarization is neglected [71], [72]. A schematic representation of the SPM during the discharge process is given in Fig. 3 below [43].

To apply the SP model to rapidly varying currents and dynamic scenarios, electrolyte diffusion, and conduction processes are included in the modified SP models [10], [14]. Different discretization techniques such as three parameter parabolic method, Padé approximation method, and finite

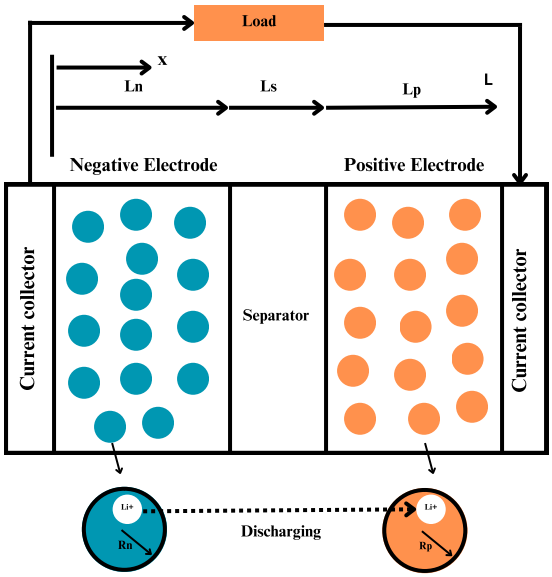

FIGURE 3. Schematic representation of the SPM during the discharge process.

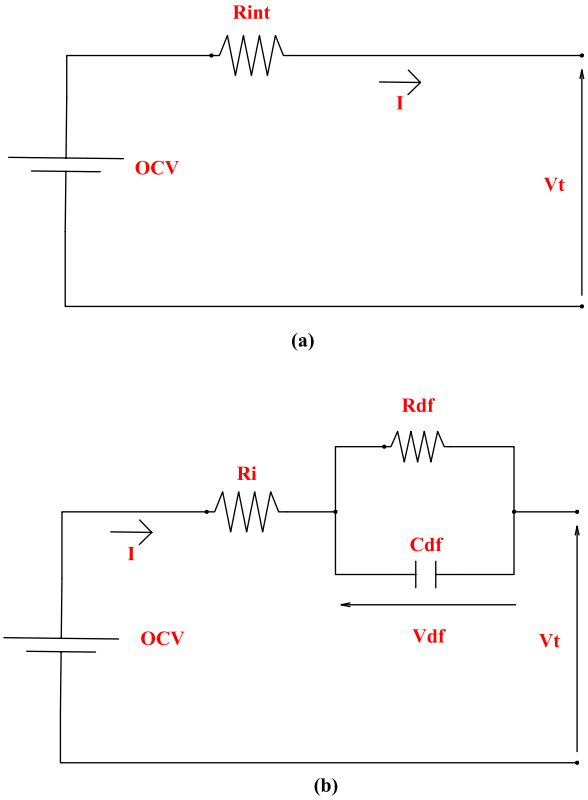

FIGURE 4. Battery equivalent circuit models (a) Rint model, (b) 1st order model [76].

different method have been used to obtain the simplified SP models (SSP) [13], [61]. These models not only achieve high accuracy but also improve model adaptability to conditions that have rapidly varying currents. The SP model assumes that the active material of the electrode is compact and uniform, however, the actual electrodes have a porous structure that impacts the movement of lithium ions. The authors of [73] and [74] have improved the accuracy of the SPM predictions by accounting the impacts of electrode porosity. The SP model also assumes that the electrode-electrolyte interface is a simple ohmic contact. The accuracy of the SPM predictions can be increased by modeling the electrode-electrolyte interface using further advanced models such as the modified Randles-Sevcik model [75].

B. EQUIVALENT CIRCUIT MODELS

The ECM of a LIB represents the battery as an electrical circuit consisting of a network of basic circuit elements such as resistors, capacitors, and voltage sources that approximate the electrochemical and physical behavior of the battery in addition to its dynamic characteristics. The order of the circuit is found to determine the performance of the model [61], [76] and can be a trade-off with complexity where a complex circuit network can consequently increase the computational burden.

The ECM is widely used in the BMS and especially for fault diagnosis, considering the model complexity and computational accuracy. Parameter estimation methods can estimate and identify the parameters which can reflect the physical characteristics such as internal resistance and capacity. In basic form, a fault detection algorithm will compare the parameter values to that of the non-faulted system to generate residuals to determine a faulty condition. Due to the strong non-linearity of the battery system, the nonlinear parameter estimation methods such as the recursive least square (RLS) method, particle filter, and genetic algorithm have been used to estimate and identify the parameters [57].

ECM can be categorized as integer-order models (IOMs) and fractional-order models (FOMs) [38], [76]. It is feasible to develop battery models that can be used for the management, control, and optimization of batteries using both IOMs and FOMs. The use of the IOMs or FOMs may depend on the application and is discussed in the next subsections.

1) INTEGER-ORDER MODELS

Ordinary differential equations (ODEs) are used in IOMs to represent the behavior of the LIBs. IOMs have integer-valued derivatives for state variables, such as battery voltage and charge level.

Fig. 4 shows the basic form of IOM circuits used to date [17], [18], [19]. In Figure 4 (a) the simplest form, which is the Rint model consists of an ideal voltage source connected in series with a resistance, however, this model fails to exhibit the diffusion mechanisms [24]. After the Rint model, Thevenin models have been proposed by the authors of [77] and [78] by adding parallel connected resistor-capacitor (RC) tanks. The number of RC tanks defines the order of the ECM circuit and accordingly, 1^{st} order, 2^{nd} order, and n^{th} order models have also been proposed [24].

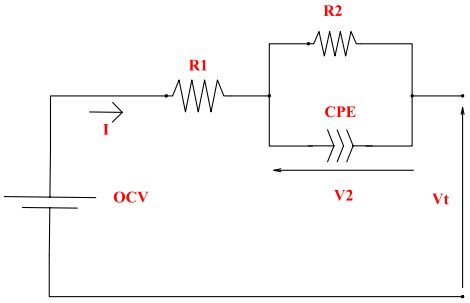

FIGURE 5. Structure of fractional order model [76].

The simple 1^{st} order model has been found to be accurate enough for many real-time implementations. The RC network consists of a capacitance C_{df}, representing the polarization of the metal electrodes, and a resistance R_{df} which represents the contact of the electrodes with the electrolyte. To have a better representation of the battery dynamics, additional RC tanks can be added to 1^{st} older models. However, more RC tanks complicate the parameter identification problem. Compared to the electrochemical models, these models are found to be suitable for real-time implementation as they can be executed rapidly and have a simple implementation.

2) FRACTIONAL-ORDER MODELS

Fractional-order models (FOMs) use fractional calculus to depict the behavior of the battery. Fraction-order models were proposed as pure RC tanks and are not capable to reflect the electrochemical characteristics (charge transfer reaction, double layer effect, mass transfer, diffusion, and other electrochemical processes) of a battery in the whole frequency range. These models were developed by replacing the pure RC tanks in IOM with constant phase elements (CPE) and Walberg components by the authors of [79], [80], and [81]. A typical structure of a FOM extracted from [81] is shown in Fig. 5.

FOMs assume that the derivative of the state variables can take fractional order values. FOMs achieve higher accuracy as they reflect the physical phenomena closely. However, The CPE characteristics are difficult to process in the time domain and therefore fractional calculus theories such as the Grunwald-Letnikov definition, Reimann-Liouville definition, and Caputo definition are used [82]. The authors of [79] propose a SoC estimator for LIB based on the fractional order impedance spectra model. The model was derived based on the characteristics of CPE and Warburg elements for the wide range of frequencies. The results show that the SoC estimation can be obtained with less than 0.5% error. Similarly, the authors of [83] propose a state of power (SoP) estimation for the LIBs based on FOM approach. The experimental results show that the maximum error of SOP estimation results is 1.34%.

A novel fractional variable order model is proposed in [84] which can be applied in the applications in electric vehicles based on voltage-current characteristics of lithium batteries. This model evolves from the typical $2^n d$ order equivalent circuit model where the new method can obtain the continuous order change, unlike the conventional RC branch which can only vary between integers.

C. DATA DRIVEN MODELS

Data-driven methods use black-box models which can be used as a mathematical model for LIBs, and also for deciding weight parameters to represent battery characteristics. These models use a training data set and in certain instances are recognized as more adaptable and efficient [85]. Although they use external measurements or the characteristics such as voltage, current, and temperature, they have good adherence to non-linear electrochemical reactions as they are capable of extracting hidden information with the support of machine learning (ML) approaches. A typical process of establishing the data-driven model [85] is shown in Fig. 6. As Fig. 6 illustrates, following the collection of enough sample data for the training data set the data-driven model can be established through the training process with ML approaches. These models can directly reflect the relationship between input (I, T, SoC) for the output terminal voltage (U).

Artificial neural networks (ANN) [86], support vector machines (SVM) [87], and long-short-term memory network [88] are some of the ML approaches which have been developed and provide better accuracy. Though these approaches contain a good performance against nonlinear problems like battery electrochemical processes they are still can easily be influenced by the training methods and the training data set [4]. In addition to the ML approaches dynamic simulation technologies such as three-dimensional active Monte Carlo simulation are also used which can explain internal behavior and reveal the structural evolution [89].

IV. PARAMETER EXTRACTION METHODS FOR ELECTROCHEMICAL BATTERY MODELS

For precise model-based battery state estimation and the optimal control design, parameter extraction of the electrochemical model is also crucial. Identification of all these model parameters is a crucial but difficult process because the PDEs within P2D models involve numerous physical parameters. First off, the manufactured battery specification sheet from battery manufacturers typically not revealing the essential information. In addition, the observable signals such as temperature, current, and voltage exhibit complex nonlinear relationships with these parameters. The parameterization goal would be made more difficult by the fact that the parameter identifiability would change depending on the operating conditions. Third, a variety of pricey tools are needed for characterization in order to measure these properties. Further, it is an obvious fact that the parameters are varying and are specific to each cell design. Therefore, not all parameters could be interchanged between different cell designs. In many related works the model parameters are matched with measured terminal voltage where the terminal voltage is sensitive to the initial set of the model parameters. These

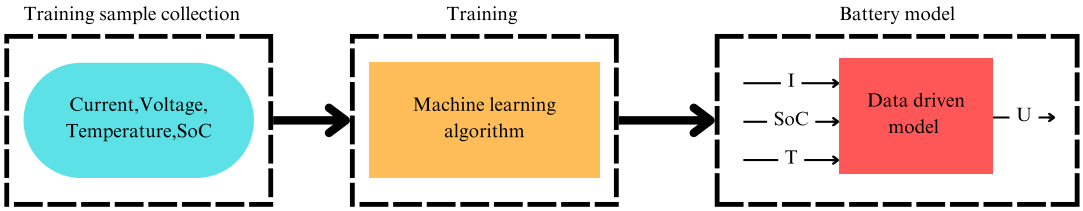

FIGURE 6. A typical process of establishing the data-driven model [85].

parameter sets are typically taken from the literature in many relevant studies; however, the sources of these parameter sets are rarely identified. Measurement of these factors through experimentation is a common alternative [90], [91], [92].

A. KEY PARAMETERS IN ELECTROCHEMICAL BATTERY MODELS

Electrochemical models achieve high accuracy; however, the model parameters need to be determined with precision. The key parameters that are used in electrochemical models of lithium-ion batteries to describe the behavior of the battery include:

Diffusivity ($D_{s/e}$)**:** Diffusivity also referred to as the diffusion coefficient describes the rate at which lithium ions diffuse through the solid phase (electrodes) and the electrolyte. This depends on the properties of the solid phase active material and the electrolyte.

Transfer coefficient (α)**:** It describes the rate at which lithium ions transfer across the electrode-electrolyte interface. It is usually given as a dimensionless number between 0 and 1, and it depends on the properties of the electrode and the electrolyte.

Solid-state conductivity (σ_s) ***[S/m]:*** This parameter describes the rate at which lithium ions move through the electrodes in the solid state and depends on the properties of the active material.

Pore wall flux (j): Pore wall flux of lithium ions, which is independent of the active surface areas of the electrodes and the applied current

Specific surface area of the electrode (a) ***[m2 m–3]:*** is the specific interfacial surface area of the solid particles.

Volume fraction of electrolyte (ϵ_e)**:** In some references this is referred to as the porosity of the media. It is calculated as the ratio between the pore volume in the selected pressure range and the sample volume, which can also be taken from the mercury porosimetry data.

Open-circuit voltage (U_{cell}) ***[V]:*** It is the voltage of the battery when it is not being charged or discharged. This usually depends on the open circuit potential of the anode and the cathode which is a function of stoichiometric number.

Capacity (Q_{cell}) ***[Ah]:*** This parameter describes the amount of energy that can be stored in the battery. It is usually given in units of ampere-hours (Ah) or watt-hours (Wh) and it depends on the properties of the electrode and the electrolyte.

B. EXPERIMENTAL TEST METHODS FOR LIB CHARACTERIZATION

There are several methods that can be used to estimate these parameters of an electrochemical model of a LIB. Some of the most common methods include:

1) **Electrochemical Impedance Spectroscopy (EIS):** This method involves measuring the complex impedance of the battery as a function of frequency and using this data to estimate the parameters of the model [93], [94], [95].
2) **Open-circuit-voltage (OCV) test:**The SoC level and temperature have significant effects on the OCV voltage. This test initially starts with a complete charge of the battery and then discharge current corresponding to 5% of SoC is applied with a rest time to relax the battery. The same procedure is applied during the charging. The flowchart for the OCV test is given in Fig. 7 below.
3) **Hybrid Pulse Power Characterization (HPPC):** Battery dynamics are assessed using the HPPC test under different operating conditions (temperature, SoC levels, charge/discharge current). The HPPC test enables the determination of battery parameters that are related to ohmic effect and charge-transfer reactions [14]. It entails applying a set of varying-amplitude alternating charge and discharge pulses at each SoC level in order to generate a transient waveform which is then used to estimate the battery model parameters [14], [96], [97].
4) **Pulse Discharge (PD) Test:** In the PD test initially the battery is charged with constant-current constant-voltage (CCCV) protocol at the ambient temperature. Then it is incrementally discharged in the steps of 5% SoC from the 100% SoC state to the lower cut-off voltage point. At the end of each current pulse, a 2-hour relaxation time is typically used to bring the battery state to thermodynamic equilibrium.

C. PARAMETER ESTIMATION METHOD FOR ELECTROCHEMICAL BATTERY MODELS

The classifications proposed for the parameter estimation methods differ between battery types. Parameter estimation techniques found in the literature are mainly for the electrochemical or equivalent circuit models while parameter estimation of thermal and aging models appear to garner

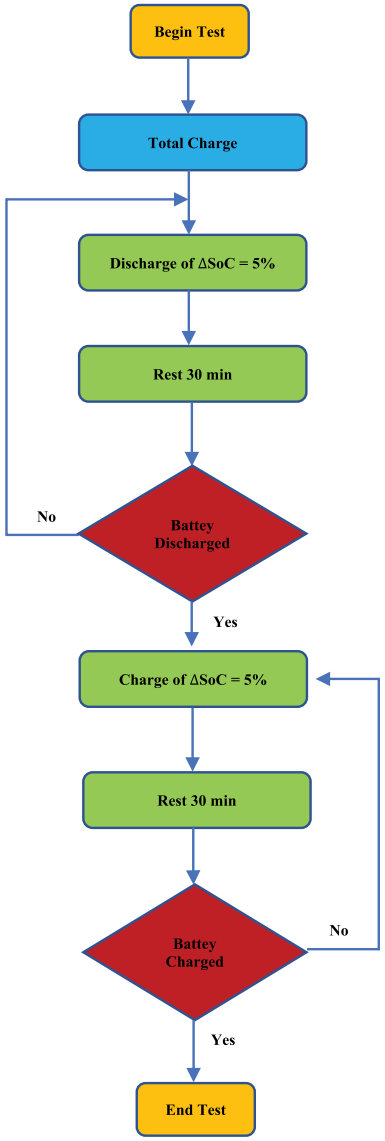

FIGURE 7. Flow chart for OCV Test.

lower priority. Accordingly, Parameter estimation method can be classified as;

1) Online identification methods
2) Offline identification methods
3) Analytical or numerical calculation methods

Analytical or numerical calculation methods for parameter extraction is directly derived from the physical principles of the LIB battery cells while online and offline identification methods utilize the experimental techniques. Online methods allow estimation of parameters/state during the normal operation of the battery system while offline methods estimate the selected parameters using specific experiments during which the battery is removed from the system.

In a BMS, the battery state variables are estimated online, and certain fixed parameters are obtained using offline techniques. This is because the parameters are usually estimated via dedicated laboratory tests before they are installed in the applications. This is frequently the case for the open circuit voltage (OCV), which is estimated when the battery is not operating over a long period (usually at least 30 min) [98].

D. ONLINE IDENTIFICATION METHODS

1) ONLINE ESTIMATION OF STATE VARIABLES

Online identification methods are mostly preferred for the equivalent circuit which represents the electrical behavior of the battery. The battery SoC changes continuously when the battery is in use. Therefore, online identification methods are mostly applied to estimate the SoC during the typical operation of a battery. The SoC will affect any or all of the other factors, and their estimation can be done online or offline (as in mixed methods).

The main important characteristics that online methods have to guarantee are as follows:

- To allow real-time execution it should have the computational simplicity
- Ability to estimate all the states using only measured information such as current, voltage, and temperature.
- Ability of estimation of all the states especially under the normal operation

Several strategies have been put forth in recent years for SoC estimation. The fundamental technique is Coulomb counting, which involves integrating the current. In addition to the challenge of calculating the initial SoC, this technique suffers from all the issues related to the drift of the integral. Some researchers have suggested adding a term obtained by PI regulators to the coulomb counting as a solution to this issue [99], [100]. Since the SoC and OCV are related, numerous methods have been researched to estimate the OCV first, and then the SoC using the OCV and the data from offline experiments [4], [28], [101].

Numerous nonlinear state estimation techniques and adaptive filters have also been used to estimate the internal state of a battery. They can be categorized into three sections as mentioned below [102].

1) Filter based method [103], [104], [105], [106], [107], [108], [109]
2) Observer based method [110], [111], [112], [113], [114]
3) Data-driven method [28], [29], [31], [34], [115], [116]

Kalman Filter (KF), Luenberger observer, Proportion Integration (PI) observer, H observer, and sliding-mode observer are examples of common algorithms [117] used for the state estimation. A typical block diagram for model-based state estimation is given in Fig. 8.

As discussed previously P2D model is more suitable to analyze the internal physical processes whereas the SPM is more suitable for state estimation, particularly for SoC estimation. The authors of [118] consider the SPM in state-space form with only eight parameters and estimate the SoC using Iterated Extended Kalman Filter (IEFK). It has been reported in [85] a nonlinear geometric observer is created to estimate

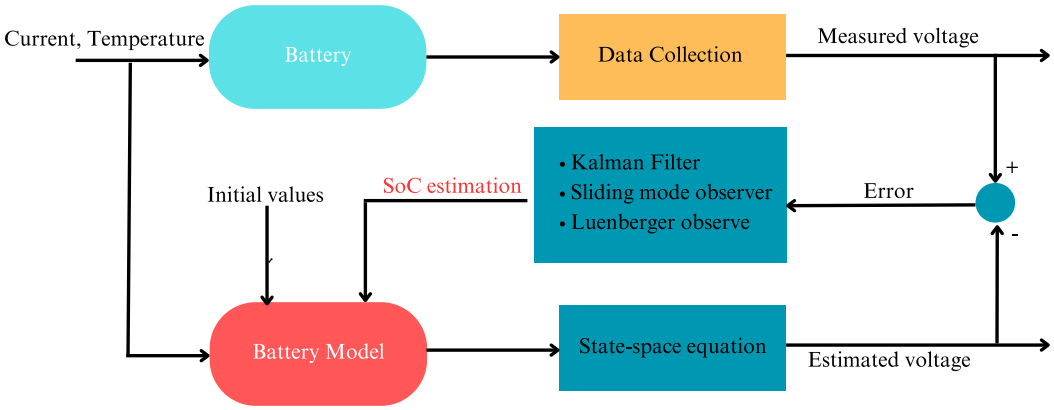

FIGURE 8. A general flow chart for model-based state estimation [117].

SoC based on SPM, and it achieves a SoC estimation with the error of less than 4.5%.

In [119], a novel electrochemical model was proposed for the SoC estimation. In this work, a projection-based method with optimized orthonormal basis functions is used to reduce the complexity of conventional P2D models. A novel moving window filter is proposed which achieve rapid convergence compared to typical state filtering method such as KF, EKF. The moving window-based filer algorithm uses more data points to estimate the battery state whereas typical state filters such as KF or EKF utilize a single time point for the state estimation. The authors of [119] demonstrate that the convergence time is reduced from 30 mins to less than 2 mins using this approach.

2) ONLINE ESTIMATION LIB PARAMETERS

In contrast to the electrochemical model used for the online parameter estimation the authors of [56] proposed a novel reduced-order electrochemical model which combines the P2D model and SPM together for the online SoH and aging parameter estimation. The SoH is often recognized by a reduction in cell capacity and an increase in internal resistance [115]. These changes are primarily brought on by undesirable side reactions, which eventually result in the loss of lithium ions and active materials, the consumption of electrolyte solvents, and an increase in the thickness of the solid electrolyte interphase (SEI) layer. As capacity fading is one of the most frequent indicators for degraded battery cells, the SoH can also be defined based on the capacity [56]. Accordingly, the SoH is given by:

$$SoH = \frac{Q_{aged}}{Q_{fresh}}. \tag{8}$$

where Q_{aged} and Q_{fresh} are the aged capacity and the fresh capacity of the cell. The authors of [56] use a SPM for the cathode and in contrast, a P2D model for the anode. Since many side reactions occur at the anode at different stages of the degradation across the thickness direction as well as increasing intensity toward the separator it is assumed that the negative electrode has 13 particles whereas the positive electrode has only one particle. The proposed model considers SEI layer formation and lithium-ion plating as two major degradation mechanisms. The initial SEI layer is created when the cell is charged for the first time to protect graphite from further reactions with the remaining solvent in the electrolyte. As the battery cell ages the pores of the particles are covered with the SEI layer which leads to a decrease in the accessible electrode surface area and increases the internal impedance. Lithium plating usually occurs acutely at sub-zero temperatures or under high charging C-rates when ion diffusion inside the solid particles is slow. In these circumstances, the surface solid-electrolyte potential difference becomes negative, especially near the separator, which causes lithium ions from the electrolyte to be reduced to metallic lithium, which deposits on instead of intercalating into the anode particles [52], [56]. A particle filter was used to estimate the SoH and aging parameters of this model. The particle filter is considered to be an effective approach for state estimation in non-linear and non-Gaussian systems and the adoption of a particle filter in [56] can be considered as a novel approach. More information about the particle filter algorithm can be found in [29], [120], and [121]. The SoH and aging parameter estimation and the capacity and power fade estimation errors are reported within 3%. and 4%, using this approach.

The authors of [29] propose an electrochemical-thermal-neural-network (ETNN) model to estimate the SoC and the state of temperature (SoT) of the battery. Initially, a sub-model with SPM and a thermal model are used to estimate the temperature and the terminal voltage approximately. With the support of the neural network, the accuracy of the parameters obtained from the sub-model is improved. Accuracy and capability for generalization across a range of temperatures is demonstrated, and the ETNN model is shown to perform better than the basic electro-thermal model. The authors of [29] also combine the ETNN model with an unscented Kalman filter (UKF) to estimate the SoC and SoH. The results show that RMSEs of steady state SoC are less than 1% for a wide temperature range from -10 – 40 °C. The SoT estimation error is found to be within 1.08 °C.

E. OFFLINE IDENTIFICATION METHODS

Under the offline estimation methods estimating the parameters for a physics-based electrochemical model generally contains two methods first is physical parameter estimation to estimate the parameters like electrode dimension, particle size, material composition, etc. by cell tear-down and the second is laboratory experiment to obtain parameter values which are directly link to internal dynamic processes of the battery.

1) PHYSICAL OR DIRECT PARAMETER ESTIMATION METHODS

Physical parameter estimation involves tearing down the cells under an argon atmosphere and measuring the physical properties. In the event the manufacturer data is unavailable or unreliable, this method is used to obtain the parameters by a number of researchers [46], [47], [48].

In [122], to determine particle radius, tortuosity, and porosity of the electrode and the separator, Hg-porosimetry was used. Conductivity and diffusion constants of the electrolyte as well as the conductivity of the active material were measured by detecting the voltage response to a DC current. Finally, the open circuit voltage curves, diffusion coefficients, and charge transfer kinetics of the electrodes as well as their balancing are obtained using experimental measurements on a coin-cell [122]. The model parameters that have been identified are listed in Table 2.

A similar approach was adopted by the authors of [123] and [124] which determines all the parameters required for the parametrization of a physicochemical model of a LIB. They have shown that the characteristics of a full battery cell can be obtained by parameterization of individual material properties. The authors directly determine the transference number of the electrolyte and the conductivity of the electrode material while other parameters are obtained from literature. The direct measurement of parameters requires an advanced experiment set up and it is time-consuming. Therefore, these methods are not very popular to implement an electrochemical model of LIB.

The authors of [125] also used tear-down analysis of LIB for parameter estimation. In this work, 35 extensive parameters were identified under physical, chemical, and electrochemical categories and are validated at different C-rates (which is defined as the charge/discharge current divided by the nominally rated battery capacity). And the Root mean square error (RMSE) between the 36 mV to 46 mV range is achieved. It is found that, among the 35 parameters, only 8 parameters have to be refined to improve the accuracy.

2) PARAMETER ESTIMATION WITH OPTIMIZATION ALGORITHMS

Parameter identification of LIBs can be considered a nonlinear optimization problem. Metaheuristic algorithms (i.e., search-based optimization methods) have been adopted by researchers [126], [127], [128] which demonstrate high performance compared to the gradient-based approaches. Typically, the gradient-based approaches rely on the gradient information of the function to guide the search, while search-based optimization does not rely on the gradient information, but instead explores the solution space through different search strategies.

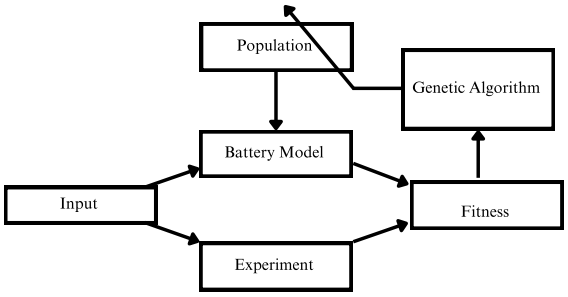

FIGURE 9. Optimizing the parameters via GA [126].

Estimating the electrochemical parameters of a P2D model indicated in Table 1 based on genetic algorithm (GA) has been investigated by the authors on [126] and [129]. GA is a stochastic search, learning, and optimization technique and mimics the biological evolution process, including mutation, crossover, and selection, on the basis of the concept that ''good individuals survive and breed good individuals''. Using the GA-based optimization technique, battery parameters can be extracted [129] by using the charging and discharging data. A typical block diagram for this is shown in Fig. 9.

A GA-based parameter estimation approach was proposed in [126] where it identified the parameters of the P2D model considering the voltage/ current cycling data and the average relative voltage error was 5%. Later the authors of [127] introduce a parameter estimation approach to estimate 7 model parameters ($D_{s,n}$, $D_{s,p}$, $\epsilon_{e,n}$, $\epsilon_{e,p}$, $\epsilon_{e,s}$, $\epsilon_{s,n}$, $\epsilon_{e,p}$) using GA for a wide range of temperature and current. In this work, a simplified electrode-average model is obtained from polynomial approximation. Compared to that of [126], this method has better performance with an average relative voltage error of 0.2%.

Rahman et al [128] have identified four parameters that show significant variation during severe or abusive conditions such as over-discharge or over-charge of a battery of a P2D model using Particle swarm optimization (PSO) algorithm. The obtained parameters are the solid diffusion coefficient and interfacial reaction rate of the negative and positive electrodes. The appropriate battery models for both healthy and deteriorated batteries were then constructed using the identified model parameters. By comparing the model output voltage with the experimental output voltage under the specified operating circumstances, these models were then verified. The identified Li-Ion battery electrochemical model parameters are within reasonable accuracy as evidenced by the experimental validation results.

In [9] electrochemical parameters which include the active surface areas of the electrodes, the diffusion coefficients in

TABLE 2. Model parameters [122].

Property type	Cathode	Anode	Seperator	Electrolyte
Geometrical Data	• Length • Width layer thickness	• Length • Width layer thickness	• Length • Width layer thickness	
Material Properties	• Porosity • Inactive part • Particle radius • Electrical Conductivity • Stoichiometric Li^+ concentration • Utilization • OCV curve	• Porosity • Inactive part • Particle radius • Electrical Conductivity • Stoichiometric Li^+ concentration • Portion of SEI • OCV curve	• Porosity	• Electrical conductivity • Equilibrium concentration
Transport Properties	• Diffusion coefficient	• Diffusion coefficient		• Diffusion • Transport number Li^+
Electrode Kinetic	• Tortuosity • Exchange current density • Charge transfer coefficient	• Tortuosity • Exchange current density • Charge transfer coefficient	• Tortuosity	

the solid phase, and the reaction rate constants were determined using the convergent bacterial foraging optimization algorithm (BFOA). Volume-average integration method and three-parameter volume average method were used to simplify the SPM model and electrochemical characteristics which are determined by the model estimated parameter are identified by the BFOA. It has been observed that the maximum terminal voltage error is 18 mV for the current-generated mutation. The maximum error is due to voltage mutation points due to the influence of resistance at current mutation points. Further simplification of SPM is proposed in [130] based on the following assumptions;

1) The non- uniform reaction distribution effect inside the electrode is neglected, and the pore-wall flux density is approximately calculated by the operating current density.
2) The physical property is approximated by a single particle, and the electrolyte and solid- phase concentration distribution can be considered to approximately obey the parabolic profile.
3) The degrees of reaction polarization of both electrodes are the same, as well as the solid-phase diffusion process.
4) The effect of battery internal temperature on model parameters is neglected at room temperature.

An automatic parameter estimation method for LIB at the beginning of the life (BOL) is proposed in [131] to estimate the parameters without postmortem analysis using a reduced-order P2D model (ROM). After grouping the parameters of ROM three parameters were selected among the 20 parameters as the most sensitive parameters for the charging/discharging and SoC. The three parameters are film resistance and solid phase diffusion coefficients of positive and negative electrodes. After obtaining the parameters with different charge and discharge experiments (C/5, C/2, 1C & 2C) a GA was used as the optimization method with multi-objective functions After validating the results with repetitive cycles, it has been observed that the error is below 12 mV.

In contrast to SPM, eliminating the redundant parameters is also has been proposed as a method to reduce the number of parameters to be determined. The authors of [47] proposed a Lumped-parameter model (LPM) which has been obtained by eliminating the redundant parameters which are geometric related. The full-order P2D model was reformulated to have 24 parameters from 36 parameters by eliminating the redundant parameters. Several transfer functions were derived to capture the response of state variables of the cell against the applied current in the LIB cell. These transfer functions are derived considering only the assumption of linearity. In order to capture the cells' dynamic behavior more accurately Constant Phase Elements (CPE) were added to the transfer functions in this work as a novel concept. In addition, to improve the fidelity of the proposed model impact of the electrolyte concentration on its potential also has been considered. The same authors further improved their model in their second paper [46] proposing a stepwise parameter identification approach based on the LPM using simple tests. These tests introduce a reference electrode in the reformulated LPM that has been converted to a frequency response initially. The reference electrode was introduced to for distinguishing the parameter value for the positive and negative electrodes. Four different tests with eight steps listed below were proposed based on the frequency

response and electrode decoupling. For both positive and negative electrodes, the single-electrode voltages are individually with the support of the reference electrode in each test. Then by applying the particle swarm optimization (PSO) algorithm parameters were estimated. The parameters identified have an error less 5% and the terminal voltage predicted from the model has an error less than 3% to the actual figures.

In many literature, the SMP [29], [132], extended single particle model (ESPM) [133], [134], multi-particle model (MP) [67], [135] models were proposed as simplified models of the P2D model. All of these models neglect some physical processes inside the LIB cell and therefore the accuracy of these models is still low compared to the P2D model. Though they are simplified versions of the P2D model, from the mathematical point of view these models are still complex with several PDEs involved. As a result, a concentration-dependent solid-phase diffusion model with lumped parameters and reduced order thermal coupling is suggested [136]. Comparing the proposed isothermal electrochemical model to other battery electrochemical models, there are only 11 unknown lumped parameters in the proposed model. The model parameters were categorized as slow-dynamics (SD), fast-dynamics (FD), and thermodynamics (TD) parameters. Here SD parameters referred to the diffusion process, whereas FD and TD parameters referred to the ohmic effect and static performance of a LIB respectively. Following the categorization, the different dynamics were extracted from the measured data of the planned experiments in order to carry out stepwise parameter identification. Finally, a galvanostatic test conducted between 25 and 45 degrees Celsius served to validate the model. The RMSEs for voltage prediction and temperature prediction, respectively, are within 79.2 mV and 1.98 °C of the measured data.

Though there are many previous studies that estimated parameters for the electrochemical and thermal coupling models, a lack of interest was given to identifying the parameters related to heat generation. In [137] a two-step parameter identification method with the square-root cubature Kalman filter was proposed. In this work not only the full set of electrochemical model parameters were identified but also the parameters related to heat exchange and generation also were identified. Initially, the extended single particle model (ESPM) proposed by [138] was converted to a reduced-order model using a pseudo-spectral approach. The pseudo-spectral method is another numerical method to solve PDEs and it has been used instead of finite different methods to reduce the number of discrete nodes. It has been identified that in the reduced order model the computation time for discharge voltage is within 1.5 s which makes sure that the model is suitable for parameter identification and real-time state estimation. 21 electrochemical and 4 thermal parameters were identified using Ant lion optimizer. In their results the voltage RSME is less than 30 mV and the temperature RSME is 0.1097 K in the IUDDS test.

With the recent developments of artificial intelligence date-driven parameter estimation also becoming the recent research focus. These methods require a large volume of data for training and validation. Despite their high accuracy, those models are computationally and memory expensive.

In [139], a neural network and genetic algorithm combination was proposed as a new method for parameter identification. In order to determine the relationship between the input current (a known parameter) and its corresponding voltage, this method employs a 1-dimensional convolutional neural network (CNN). With the help of data generated during GA operation, the correlation between the model parameters and the current and voltage was established. The dynamic properties of the P2D model are present in the data simulated by the GA procedure. Electrolyte porosities of the electrodes and the separator were taken into consideration as capacity-related factors, and the dynamics parameters, which include solid diffusion coefficients, reaction rate constants, and an SEI resistance, were chosen as dynamic parameters.

Although there are numerous additional capacity-related parameters, such as particle radius, electrode thickness, maximum lithium concentrations at the electrode, and current collector, in this study, they are regarded as known parameters because they are chosen by the manufacturer during the design of the cell. The output voltage RMSE and the parameter MPE were both dropped by 0.761 mV and 13.71%, respectively, after the proposed technique was confirmed using both experimental and synthetic data. Additionally, a 6.496 mV reduction in the output voltage RMSE for the experimental data was achieved. Another data-driven parameter estimation framework is proposed in with the cuckoo search algorithm [140], [141], [142]. Parameter sensitivity analysis was conducted to categorize the parameters into three groups with high, medium, and low sensitivity. This method only considered the current and voltage profile data to estimate the parameters. As a new concept in order to reduce the estimation errors of capacity-related parameters capacity error between two electrodes was also considered other than the voltage error in the model and cell. A multi-step parameter estimation approach was used considering the different sensitivities which increases the accuracy of low-sensitive parameter estimation. With the use of the cuckoo search algorithm, a higher convergence speed was obtained compared to the other meta-heuristic methods for parameter estimation. The proposed data-driven strategy minimizes the voltage error under low and high load dynamics by 82.0% and 59.6%, respectively, in comparison to the experimental identification method also reduces the capacity error between two electrodes to 95.4%.

A two-phase surrogate model-based parameter estimation (TPSMA-PEAL) algorithm was proposed in [34]. This model has been implemented to obtain the parameters ($D_{s,n}$, $D_{s,p}$, D_e, k_p, k_n, t_+^0)of a P2D model by combining a reduced order model and a data-driven model. To eliminate the redundant parameters a reduced-order model was implemented initially.

Then the data-driven model was used for the parameter estimation. The proposed TPSMA-PEAL method has overcome two major challenges in parameter estimation which are the over-fitting problem and the low observability of some parameters. The relative error for estimated parameters is in the range 4-5% as observed from the simulation and experiments. It was also identified by the authors that this method is having difficulty in on-board implementation BMS due to high computation power and storage space. They also have been identified that it can be improved with the support of cloud computing.

F. ANALYTICAL OR NUMERICAL CALCULATION METHOD

As previously mentioned, the third family of identification methods is based on analytical modeling or finite element calculations. These methods should be offline. However, because they are not based on the results of experimental tests, it is preferable to classify them separately. Indeed, the calculations could be repeated as functions of some measurement (i.e., current, voltage, or temperature) and could be used to tune the parameter values. In this case, they could be used online.

G. VALIDATION OF ESTIMATED PARAMETERS

It's important to note that the accuracy of the parameter estimation depends on the quality of the data used, the complexity of the model, and the method used. The estimated parameters should be validated by comparing the model predictions with the experimental data, and the parameters should be updated as necessary. After obtaining the model parameters the validation of the models with estimated parameters is the final step of battery modeling. These models can be validated mainly using three different approaches. It can be based on voltage, temperature, and the parameters itself. Voltage validation is the process of comparing a cell's voltage response to a parameterized cell model. As the temperature has a significant impact on the battery behavior it also can be taken into consideration. In most of the previous methods these two methods are applied to validate the parameters. The final method of validation compares the actual parameter values to the estimated parameter values directly. The true values must be known in order to use this. This is done by simulating the P2D model for a particular input-current profile to generate synthetic simulated cell-test data, utilizing that data to estimate parameter values, and then comparing the estimated parameter values to the actual values utilized in the simulation. It has been demonstrated that some parameters of the electrochemical model are not sensitive to the cell voltage and it concludes that only voltage validation is not enough to estimate the parameters correctly. As a solution to this, lumped parameter or parameter grouping [14], [132], [143], [144] can be used as some of the parameters are identifiable but the sensitivity to measurable variables is negligible.

V. CHALLENGES & FUTURE DIRECTIONS IN PARAMETER EXTRACTIONS OF LIB BATTERY MODELS

It has been identified by the presented review in this paper that the parameter estimation method can be categorized into online, offline, and analytical methods. While online methods are basically implemented to state estimation SoC, SoT and SoH from the battery model, Offline methods are being used to estimate the electrochemical parameters of the battery model. In the offline method parameter extraction from post-mortem analysis and non-invasive parameter estimation has been widely used. Though the post-mortem analysis provides robust and accurate results the process requires many recourses and is time-consuming. As the specific equipment are required the process is costly.

As a solution to issues reported in direct measurements, non-invasive methods are proposed. The non-invasive methods are highly dependent on the sensitivity and identifiability of the model parameters. To achieve the best results, the quality of training data and the predetermined parameter variation range are essential. Currently, it is still challenging to fully identify many factors from direct current and voltage measurements. On the other hand, there are always some redundant parameters that are difficult to identify when utilizing computational methods to estimate the model parameters [90], [145]. Another issue is it's still not obvious whether assumptions made for various factors are consistent. For instance, while parameterizing a model, many assumptions are generally made. This makes it difficult to obtain accurate results as the assumptions may vary depending on operating conditions. There are no proofs to appear in the literature that the parameters related to aging are incorporated in electrochemical model parameter estimation. Therefore, it is an obvious requirement to design new identification tests which include the parameters related to the aging of LIB cells.

Though many methods are proposed in the literature to estimate the parameters of electrochemical models it is unclear whether the input-state dynamics and input-output dynamics of a lithium-ion cell will actually match in models. In this case, the models may accurately predict temperature or voltage, but there are no guarantees that the internal electrochemical variables are estimated correctly or that the parameter estimates are concise. Mixed approaches can be a very helpful tool in this situation since they take into account not only exact parameter estimates but also precise state and voltage prediction which can be used improve the accuracy of the parameter estimation of electrochemical model. These Mixed approaches combine the adaptability of data-driven models with the advantages of conventional electrochemical models. It creates the models that are more accurate than conventional electrochemical models by using both experimental data and physical concepts. Therefore, these techniques would be more robust to errors in model assumptions and parameter values. In case of applying these models in BMS for online operation it is important that these variables are correctly modeled.

VI. CONCLUSION

As a result of technological advances and rapid development of LIB and their applications ensuring the safer operation becoming popular in LIB systems. As these battery systems are operating in extreme operating conditions and harsh environments efficient and reliable BMS operation is needed to detect the abnormalities and faulty conditions. Battery modeling plays a major role in online BMS operations. This paper reviewed existing battery modeling concepts basically under the electrochemical model, equivalent circuit models, and data-driven models. Basic principles, applications, and parameters for each model were presented. It has been identified the electrochemical model is the most detailed and accurate battery model since it clearly describes the internal physical processes with several PDEs. Accurately predicting performance and aging depends heavily on understanding the battery model's parameters. As the most promising battery model parameter estimation methods for the electrochemical model were critically discussed. Parameter estimation for electrochemical models was examined under the categories of online, offline, and analytical methods. More focus was given to online and offline methods as they are widely used in real-time implementations. In each method, the state-of-the-art review was conducted to date and the implementation, applications, and limitations were analyzed. It has been identified that the mixed method which combines the online and offline methods shows a good performance compared to using them separately. The challenges and future directions for parameter estimation methods for the electrochemical model were discussed in the last section of the paper.

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