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Review

A Comprehensive Review of Lithium-ion Cell Temperature Estimation Techniques Applicable to Health-Conscious Fast Charging and Smart Battery Management Systems

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Abstract: Highly nonlinear characteristics of lithium-ion batteries (LIBs) are significantly influenced by the external and internal temperature of the LIB cell. Moreover, cell temperature beyond the manufacturer's specified safe operating limit could lead to thermal runaway and even fire hazards and safety concerns to operating personnel. Therefore, accurate information of cell internal and surface temperature of LIB is highly crucial for effective thermal management and proper operation of a battery management system (BMS). Accurate temperature information is also essential to BMS for the accurate estimation of various important states of LIB such as state of charge, state of health and so on. High capacity LIB pack, used in electric vehicles and grid-tied stationary energy storage system essentially consists of thousands of individual LIB cells. Therefore, installing a physical sensor at each cell especially at the cell core is not practically feasible from the solution cost, space and weight point of view. A solution is to develop a suitable estimation strategy which led scholars to propose different temperature estimation schemes aiming to establish a balance among accuracy, adaptability, modelling complexity and computational cost. This article presented an exhaustive review of these estimation strategies covering recent developments, current issues, major challenges, and future research recommendations. The prime intention is to provide a detailed guideline to the researchers and industries towards developing a highly accurate, intelligent, adaptive, easy to implement and compute efficient online temperature estimation strategy applicable to health-conscious fast charging and smart onboard BMS.

Keywords: electric vehicles; machine learning; Kalman filter; thermal modelling; online prediction; electromagnetic impedance spectroscopy; computational cost

1. Introduction

Lithium-ion batteries (LIBs) are widely used in electric vehicles (EVs), grid-tied stationary energy storage systems, and several other consumer electronics primarily due to their high voltage rating (>4 V/cell) and high energy density (~ 265 (W h) L^{-1}) and longer operational life. The use of LIBs in automotive and aerospace applications has led to larger cell sizes and large battery packs for a higher driving range and the requirement for more aggressive charging and discharging. However, thermal instability and temperature-dependent nonlinear behaviour are some of the common concerns behind the safe and reliable operation of LIB systems. It is noticed that the operation of batteries outside the safe operating temperature directly affects the performance of LIBs such as cycle life, efficiency, reliability and safety. Researchers investigating the thermal performance of LIB showed that the best operating temperature range is 25°C to 40°C [1,2]. Richardson et al. [3] demonstrated that the difference between the core and surface temperature could reach more than 10°C during real-life application especially during the high discharging condition and fluctuating load current demand. The excessive temperature difference and the accumulation of a large amount of heat inside the cell could lead to thermal runaway or even explosions and fire [4]. That necessitates the employment of a battery management system (BMS) for effective monitoring of battery parameters (current, voltage, temperature), estimation of battery states (state of charge (SOC), state of health (SOH), remaining useful life (RUL), state of temperature (SOT) [5]). Research studies demonstrated that SOC [6], SOH [7], and remaining storage capacity [8] are the function of temperature thus the estimation of the battery states also depends on the accurate estimation of cell temperature. The Columbic efficiency of a cell is greatly affected by the cell temperature during the charging and discharging period. Few other popular functionalities of BMS include cell balancing [9] and fault detection/diagnosis [10] to ensure optimum capacity utilization, operational safety, reliability, and longer battery life often requires temperature information of an individual cell and battery pack as well. Therefore, accurate information of core and surface temperature is highly crucial for effective thermal management and safety of LIB pack. Moreover, in cold climate areas battery capacity is drastically reduced due to low-temperature operation that requires preheating the battery to a suitable range for optimum performance [11,12]. It is also evidenced that for every 0.1°C beyond the safe operating region the battery capacity degrades by about 5% [13]. It is evidenced that maximum heat is generated during discharging period especially with fast discharging [14]. Therefore, accurate temperature estimation is essential for effective thermal management and safety during fast charging and discharging and preheating of the cell to minimize capacity fade.

In summary, it could be stated that the accurate information of cell temperature is undoubtedly serving as the essential basis for the thermal management and safety of LIB. While the surface temperature of each cell can be measured by installing a temperature sensor on each cell, the core or internal temperature measurement directly using physical sensors is challenging. Moreover, installing a temperature sensor on each cell surface is not practically feasible from a system cost, space and weight point of view as any high capacity battery pack used in EVs and grid-tied systems essentially consists of thousands of individual cells. Therefore, researchers are straggling hard to develop a high-fidelity, accurate, easy to implement, and computationally inexpensive online temperature estimation strategy suitable for low-cost onboard BMS. Several temperature estimation techniques have been proposed by researchers so far. Each different type of method has its advantages and limitations with respect to the above-mentioned features of an optimum BMS. Therefore, a summary of all the prominent techniques would be very helpful to the researchers and developers serving as a baseline for further research and as a guideline for selecting appropriate techniques suitable for a specific requirement. However, such a summary with detailed discussion on current progress and explanation of the existing issues, challenges and future research scopes has not yet been presented in the literature. Therefore, this article covered the research gap by conducting a comprehensive review of the state-of-the-art temperature estimation strategies reported in the literature so far.

The paper is organized as follows: In Section 2 generic temperature estimation strategy of LIB is presented. The classification of temperature estimation strategies is presented in Section 3. Section 4 is dedicated to presenting the existing estimation techniques, their evolutions, limitations and challenges. Section 5 discusses the current issues, challenges and future research recommendations. Finally, Section 6 is dedicated to a summary of the major findings and concluding remarks.

2. Generic Temperature Estimation Strategy

Irrespective of battery chemistry heat is accumulated inside the battery during the charging/discharging even during idle conditions majorly due to several largely exothermic chemical and electrochemical reactions as well as transport processes. If the heat transfer from the battery to the surroundings is not sufficient then the heat gets accumulated inside the battery resulting increase in core and surface temperature rise thereby risking thermal runaway. This phenomenon is even more prominent in the case of hard-cased insulated batteries (as used in EVs), under fast charging/discharging and the operation in hot environments. Heat dissipation is worse in cylindrical LIBs that are extensively used in high-capacity LIB packs. Therefore, a typical temperature estimation scheme consists of two models namely, a heat generation model and a heat transfer model [15]. Often, a battery electrical model is also used to estimate total heat generation using Bernardi's [16] heat generation model whereas few other models use a mathematical form of battery electro-chemistry to calculate the heat generation. Adaptive estimation strategies also consider the influence of different battery states such as SOC, SOH as the battery temperature is a function of these battery states. Then the heat transfer model takes the estimated total heat quantity as well as few other external measurements such as ambient temperature to predict the temperature of that cell. Closed loop estimation schemes use the measured or the estimation temperature as feedback to improve the prediction accuracy. A schematic layout of a generic temperature estimation strategy for LIB is shown in Figure 1.

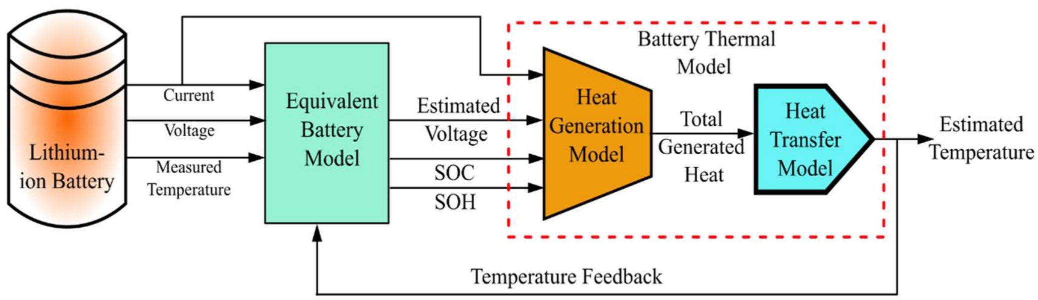

Figure 1. Schematic layout of a generic temperature estimation strategy for LIB cell.

3. Classification of Temperature Estimation Strategies

As shown in Figure 1, typically a temperature estimation scheme consists of a heat generation model and a heat transfer model. The heat generation models reported in the literature can be broadly classified from two different aspects; based on modelling strategy and based on the source of heat generation. Heat generation models based on modelling strategy can be classified into three groups, physics-based electro-chemical model [17–20], equivalent circuit models (ECM) [21–23], black-box models [24–26]. Whereas, based on the source of heat generation these models can be grouped as a concentrated model, distributed model [27] and heterogeneous model [21,28]. The concentrated heat generation model considers that all heat is generated at the core only, usually considered to reduce the modelling complexity. The distributed heat generation model consider that uniform heat is generated throughout the entire cell geometry whereas heterogeneous model can capture the different heat generation from difference cell layer usually resulted by the temperature and current density gradient inside the cell. The heterogeneous models are more detailed thus can produce highly accurate predictions however, these are most complex and require extensive experiments for modelling. Distributed heat generation models are a balance between the concentrated and heterogeneous models. The heat transfer models can be classified into Finite element analysis (FEA)-based models [23,29–32], heat capacitor-resistor models (lumped or distributed parameter) [24,33–36], and data-driven techniques. Heat capacitor-resistor-based models use the analogy between electrical and thermal systems. Heat capacitor-resistor can be further classified as mentioned in Figure 2. Lumped parameter models are simple and useful for online applications, however, only one or two average temperatures can be predicted with these models whilst the battery temperature distribution is not spatially uniform especially in larger capacity cylindrical LIB cells. On the other hand, complex distributed models [37,38] can describe the detailed temperature distribution in a cell, however, they are not suitable for online application due to their computational complexity. Several other detailed models

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of LIB accounting for the thermal characteristics of different layers are studied in the references [39–44]. A two-state/node model provides information on core and surface temperature whereas a one-state/node model can provide only core temperature.

The heat transfer model where total heat generation is one of the input parameters is collectively called the battery thermal model where total heat generation is estimated by the battery heat generation model. The thermal modelling of LIB is a separate area of study and is not under the scope of this study. It deals only with the temperature estimation strategies. However, as most of the temperature estimation strategies are extensively depending on thermal modelling thus an overview of each modelling technique is also discussed with the respective temperature estimation strategy for better understanding of the readers. Researchers employed different types of heat generation models with different kinds of heat transfer models to come up with a temperature estimation scheme. Therefore, it is challenging to classify these estimation strategies. Broadly, the temperature estimation schemes can be grouped into electro-chemical thermal modelling-based, equivalent electric circuit model (EECM)-based, machine learning (ML)-based, numerical-model based, direct impedance measurement-based, magnetic nanoparticles-based schemes. The family of the LIB heat generation model, heat transfer model and temperature estimation strategy are illustrated in Figure 2.

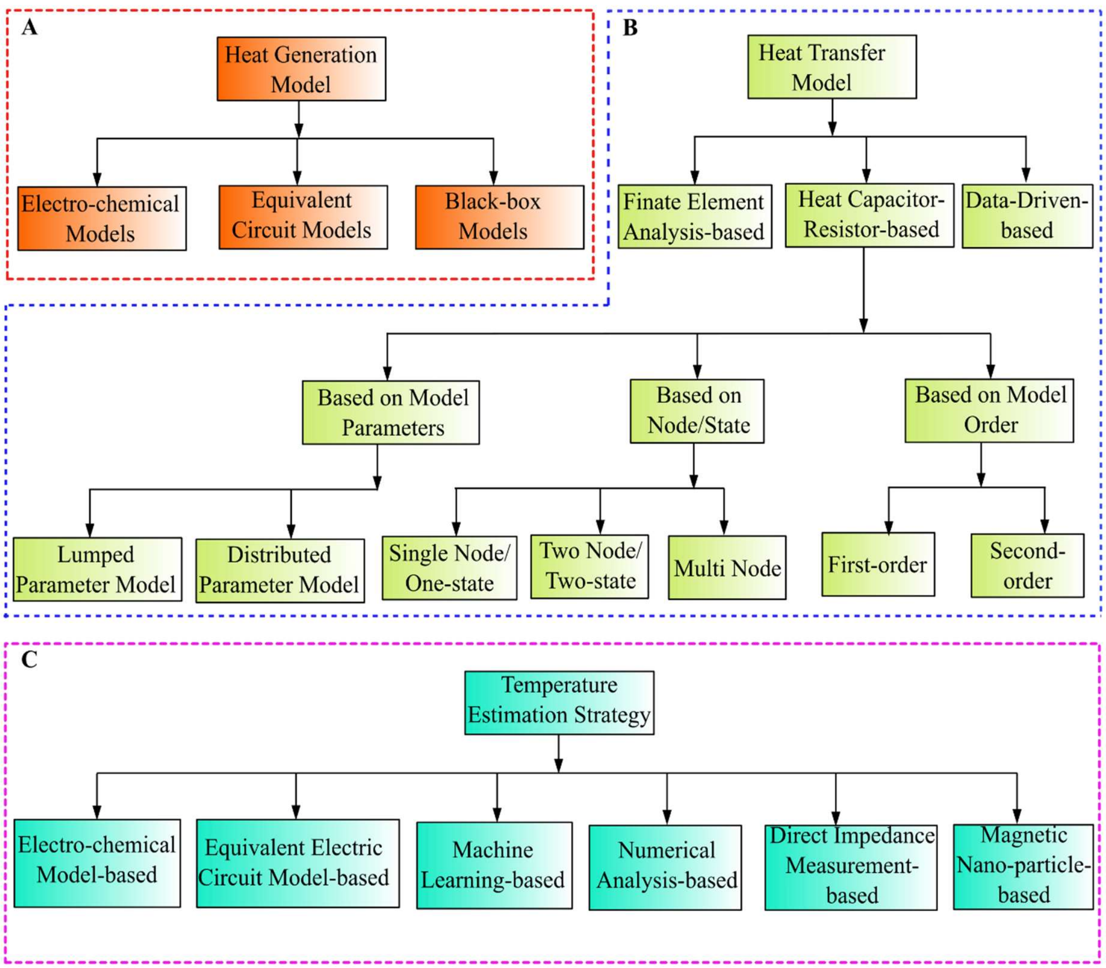

Figure 2. Family of (A) Heat generation model, (B) Heat transfer model, (C) Temperature estimation strategy.

4. Comprehensive Review of Temperature Estimation Strategies

4.1. Electro-chemical Thermal Modelling-based Temperature Estimation

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Researchers started thermal modelling in the early nineties, those are mostly coupled with an electrochemical model to simulate the temperature profile of a battery under different operating conditions, geometries or cooling rates. There are simple one-dimensional (radial direction) models [33,45–50] to complex three-dimensional thermal models [51–55]. Researchers have primarily used different analytical techniques to mathematically model the electrochemical behaviour of the cell. One-dimensional models typically assume isothermal, constant current operation of the battery and lumped thermophysical properties and constant heat generation rates. Highly complex three-dimensional models require an in-depth understanding of the thermodynamic properties of battery materials and parts to consider the heat effects caused by ohmic resistance, chemical reactions, mixing processes, polarization and electrode kinetic resistance. Often temperature estimation using such highly complex models is very accurate, however, such detailed models are essential for battery design purposes. Those are not compatible with temperature estimation using onboard BMS with low computational resources. These complex models are capable of accounting for the time-varying nonlinear battery performance. However, they typically require several system properties, operational parameters which require extensive experimental measurements. While at the same time quantitative estimation of some of the properties like transport properties, thermo- dynamic properties and heat effects are highly challenging.

Thomas and Newman [56] were introduced an electro-chemical modelling-based detailed heat generation model of LIB to estimate the total heat generation during the charging/discharging period. The model can provide accurate information on heat generation only, temperature estimation is not presented in this study. Their heat generation model was extensively used by several other researchers. Modelling is very detailed thus highly complicated and not suitable for online application owing to the computational burden. One of the widely-used Electro-chemical models commonly known as the Doyle-Fuller-Newmann model [33,57] is extensively referred to and also used for thermal modelling. It consisting of nonlinear partial differential-algebraic equations to describe the internal characteristics of LIB. It is also referred to as the pseudo-two-dimensional (P2D) model. The major limitation of the model is its high computational burden which limits its application in online state estimation in embedded BMSs. Here, Al Hallaj et al. [49] showed that a simplified transient one-dimensional thermal model with lumped parameters is sufficient for cell design purposes especially to simulate the thermal behaviour of scaled-up LIBs. Detailed knowledge of the role of different cell components such as electrodes, electrolytes and separators in heat generation is also not necessary. While few researchers used this type of complex electro-chemical model to explore pulse power limitations to prevent thermal runaway and to design thermal management systems [58,59]. Those are mostly used for LIB cell as well as LIB pack designing. A lumped electrochemical-thermal-coupled model was used to predict the thermal performance of LIB alongside the performance of individual electrodes at various operating temperatures by Fang et al. [60]. The model was validated against the experimental data for constant current and pulsing conditions characteristic of HEV which are merely providing the laboratory experimental results instead of real-work application scenario. The impact of charging current on internal temperature behaviour was investigated in reference [61]. Gerver et al. [62] included more detailed information and cell characteristics to develop a multi-dimensional electrochemical thermal model of LIB to analyze the thermal performance and heat generation more accurately. Despite estimation accuracy, the modelling complexity and computational burden limit its application in embedded BMS.

Due to a lack of clear understanding of the electrochemical processes inside the LIB and their corresponding mathematical equations alongside to reduce the computational expenses, often all heat generation sources were not modelled/considered. These unmodeled heat generation behaviours lead to significant errors in temperature estimation. Regarding this, Zhang et al. [63] developed a two-state thermal model utilizing discretization and inverse model techniques which do not require prior knowledge of thermal boundary conditions. Moreover, the model is capable of estimating the total heat generation of a battery cell, thus thermal modelling of each heat source is not required and abnormal heat generation can also be detected from the estimation results. The effectiveness and robustness of the model were tested for varying thermal boundary conditions and fast charging conditions. While the strategy is designed for self-heating pouch cells, a similar approach could also be adapted for other types of LIBs. Thus, further research is recommended here. A high-fidelity electrochemical model and on-board measurements such as terminal voltage and current were used by Wang et al. [64] to estimate the cell temperature at a wide range of C-rates during the charging/discharging period. They have also used a dual ensemble Kalman filter (DEKF) which incorporates enhanced single-particle dynamics to relate terminal voltage to battery temperature and Li+ concentration. Besides, modelling complexity and high computational cost, the accurate determination of lithium (Li+) concentration is challenging. Therefore, the application of the model in real-life online prediction is questionable. The spatial distribution of internal temperature in LIB was estimated using a pseudo-2-D electro-chemical model and soft-constrained dual unscented Kalman filter (DUKF) by Marelli and Corno [65]. It is mainly developed to estimate the Li+ concentration and modelling complexity and computational expenses are very high. However, the approach could be extended for temperature estimation. Smith et al. [58] have developed a one-dimensional electrochemical, lumped thermal model to explore pulse power limitations and thermal behaviour of a LIB pack. The electro-chemical thermal modelling-based temperature estimation strategies proposed by different authors are summarized in Table 1 for a quick reference to the readers. In general, the major limitations of any electro-chemical model-based strategies are the modelling complexity and high computational cost making the model unsuitable for online prediction and application at low-cost onboard BMS.

Table 1. Summary of electro-chemical thermal modelling-based temperature estimation strategies.

Reference	Types of Model	Important Note
Thomas and Newman [56]	One-dimensional electro-chemical model	Not used for temperature estimation

Doyle-Fuller-Newmann model [33,57]	Pseudo-two-dimensional (P2D) model	Not used for temperature estimation but several other researchers used
Al Hallaj et al. [49]	A transient one-dimensional thermal model with lumped parameters	Detailed information of electrodes, electrolytes and separator were considered in heat generation model
Fang et al. [60].	Lumped parameter electrochemical-thermal-coupled model	Can estimate one or two average temperatures, Performance of individual electrode at various operating temperatures, constant current and pulsing conditions characteristic were considered
Gu and Wang [37]	Thermal energy generation model, multiphase micro-macroscopic electro-chemical model	Temperature-dependent physicochemical properties and thermal behaviours under various charging conditions were considered. Capable of predicting the average cell temperature as well as the temperature distribution inside a cell
Kumaresan et al. [38]	One-dimensional thermal model	Thermal dependence of various parameters in the model on different discharge profiles was assessed
Kim et al. [61]	Two-dimensional modelling +Finite element method (FEM)	Able to provide temperature distribution based on potential and current density distribution
Gerver et al. [62]	A multi-dimensional electrochemical thermal model	Thermal properties of each cell layer are considered
Wang et al. [64]	High-fidelity electrochemical model +onboard measurements + dual ensemble Kalman filter (DEKF)	Wide range of C-rates during the charging/discharging period
Marelli and Corno [65]	Pseudo-2-D electro-chemical model and soft-constrained dual unscented Kalman filter (DUKF)	Can provide information on the spatial distribution of internal temperature
Smith et al. [58]	A one-dimensional electrochemical lumped thermal model	Adaptive to different drive-cycles, tested and validated with FUDS and HWFET drive cycles

4.2. Equivalent Electric Circuit Model-based Temperature Estimation

An equivalent electric circuit model (EECM) represents the thermal dynamics of LIB using electrical system parameters to develop a heat capacitor-resistor-based battery thermal model. Depending on the number of heat capacitors (number of energy storage elements) two types of models namely, the first-order model and second-order model have been developed so far in the literature. The first-order model consists of one thermal energy storage element whereas a second-order thermal model consists of two heat capacitors, typically one for the heat capacitance of the core and the other one is for the cell surface [66]. The second-order model can capture more dynamics than the first-order model. Further, depending on the modelling complexity, EECM could be also classified as lumped-parameter and distributed parameter models. Lumped-parameter models are used for simplification and thus low computational cost compared to detailed distributed models. Computationally efficient lumped thermal models are developed using single temperature as input to capture the model parameters [67] while some researchers used both surface and core temperatures of the cell to construct the lumped thermal models. Some also considered the correlation between cell geometry and other physical properties with thermal modelling [68]. However, several assumptions were made during modelling leading to inaccurate temperature estimation compared to detailed thermal modelling. Further, thermal models that only estimate the core temperature are considered as single-state/node [69] whereas if the model can estimate both surface and core temperature then it is termed as two-state/node [63] thermal model. The parameters of the EECM are identified through ranges of experimental studies such as electro-chemical impedance spectroscopy (EIS) or utilizing externally measurable quantities such as voltage, current, and temperature. Few studies also considered various conditions of SOC, SOH and estimated surface/core temperatures to make the model more robust. It is very difficult to group those thermal models because lumped models are used in both single-state and dual-state modelling and the model could be first-order and second other. Therefore, the literature is grouped into cell level and pack level temperature estimation schemes that are discussed below.

4.2.1. EECM-based Cell Temperature Estimation

One of the prime challenges of any EECM-based strategy is model parameter identification. Forgeze et al. [39] used transient experiments by applying current pulses of different magnitudes to increase the internal temperature and the model parameters, heat transfer coefficients and heat capacity were determined to construct a lumped parameter thermal model. This study used EIS for parameter identification where current pulses at 2 Hz were used to increase the internal temperature. The core temperature is estimated based on the measured surface temperature using the lumped parameter thermal model. The entropy change was also taken into account while modelling. The strategy developed by Forgez et al. lacks quantitative analysis of the influence of heat generation. The operating current is much higher compared to the very low current value used in EIS. Therefore, model parameters determined using EIS are not appropriate for capturing the thermal dynamics accurately. Moreover, they have considered uniform internal temperature however, more than 10°C temperature difference among different internal points of a cell has been reported in the same study. This strategy requires surface temperature measurement by installing a temperature sensor at each cell, thus scaling-up is impractical. Maleki and Shamsuri [70] developed a thermal model of notebook computer LIB-pack to understand the thermal response under various operating conditions aiming to reduce the battery pack designing cost and time. They have revealed that the temperature rise during charging is dominated by heat dissipation from the control power electronics while during discharging it is dominated by the heat generated inside the LIB cell. These relevant observations must be considered while designing an effective thermal management system of LIB pack, especially for health-conscious fast charging. Surya et al. [66] developed a second-order thermal model for core and surface temperature estimation scheme using KF. Here least square (LS) algorithm was employed to identify the battery thermal parameters. Despite the simplicity and good accuracy, environmental uncertainties were not considered during modelling. Moreover, they have presented the results based on simulation study alongside very simple and low current discharge profile was used for model validation, thus accuracy in the real-world application needs further investigation. Previously, models were validated using a simple charging/discharging current profile. However, the load profile in real-life applications much deviates from those simple loading profiles. Therefore, a second-order thermal model and ECM-based two-state thermal model of cylindrical LIB cell were validated with two basic drive-cycle tests, covering SOC range 25%-100%, temperature 5°C-38°C, and maximum C-rate of 22 by Lin et al. [71]. The influence of the constantly varying temperature and SOC on the EECM parameters and consequential effect on battery thermal performance was investigated by Lin et al. [71]. The model demonstrated good prediction accuracy and robustness. However, testing using standard internationally referred drive-cycles was not conducted. Thus, accuracy and robustness in practical scenarios need further investigation. EECM parameters are influenced by cell ageing, thus Li and Yang [72] considered the influence of influences of ageing and heat transfer conditions on the model thermal physical parameters. Li and Yang identified the parameters of the extended lumped parameter model online where a forgetting factor recursive least squares (FFRLS) algorithm was employed.

Further to this research, the uncertainties in practical operation were considered by Lin et al. [41,73] alongside the impact of cell ageing during online parameter identification. As an up-gradation, the commonly deployed LS algorithm was augmented with non-uniform forgetting factors to track the time-varying internal parameters making the model adaptive to cell ageing and other uncertainties. In reference [74] only two lumped models were used to approximate the core and surface temperatures respectively which may not be suitable for a large capacity LIB pack due to strong spatiotemporal thermal distribution. While the influence of overpotential entropy changes on battery heat generation was considered, core temperatures estimation of only a single cell was considered. Sun et al.

[75] developed a second-order lumped parameter thermal model with KF technique for core temperature estimation only (single-state). They have used ECM based heat generation model to mathematically accumulated the total heat generation at the cell core. As an improvement of previous studies, this study considered the influence of entropy changes and overpotential on cell thermal behaviour and was quantitively analyzed to develop an online internal temperature estimation strategy. This strategy utilized surface and ambient temperature for core temperature estimation during charge and discharge cycles where KF was used for adaptive estimation by the process of state and time update in real-time. The impact of unmeasurable modeling error, the initialization error and the possible time-varying external thermal resistance on the temperature estimation accuracy was considered by Dai et al. [76]. Where, a lumped parameter EENT model was developed for adaptive core temperature estimation based on KF. Further, joint Kalman filtering (JKF) was used to simultaneously estimate both core temperature and time-varying external thermal resistance online. The LS algorithm based on the experimental data was also used to determine the lumped parameters of the thermal model. Dai et al. enhanced the modelling accuracy by constructing separate thermal model for core and battery shell alongside considering the external heat exchange coefficient as time-varying. The authors simply stated that the proposed method is compute efficient, however, no information about computation time, hardware requirement was presented. Several assumptions were also made during modelling, leading to inaccurate estimation in real-life application.

A trade-off between the detailed and lumped parameter thermal modelling approaches were considered by Doughty et al. [77] and Park et al. [68]. They developed a two-state thermal model that predicts the surface and core temperature of LIB. The novel intention was to provide more information compared to the lumped model while reducing the computational cost. Few researchers also termed the lumped parameter model as a reduced-order model (ROM). Whilst, the primary intention is same, that is, to reduce the complex thermal problem into a simplified heat transfer problem characterized by a reduced set of thermal parameters. A combination of lumped parameter two-state thermal model with 2RC (second-order) ECM along with joint Kalman filter (JKF) based core and surface temperature estimation strategy was proposed by Chen et al. [69]. The simulation and experimental test were conducted to verify the adaptiveness of the model to constantly varying temperature and SOC and finally the prediction accuracy was also assessed. It was also demonstrated that the proposed model has higher prediction accuracy compared to previously discussed EECMs. It was also demonstrated that the model is highly robust against automatic correction for surface thermal resistance.

To provide more detailed information on the temperature distribution in cylindrical LIB, Xie et al. [78] developed a one-dimensional (radial) lumped parameter thermal model with a dual Kalman filter (DKF). As an improvement, this model is capable to provide temperature information at three different points of the battery, compared to only core and surface temperature. Thus, the researchers termed this modelling as a three-node thermal model. In this study, the anisotropy of thermal conductivity was also considered in identifying internal resistance and SOC during the temperature estimation to enhance the prediction accuracy and robustness. The impact of different charging/discharging current conditions was not considered. Moreover, 1-RC ECM-based heat generation model is considered, thus presumably accuracy can be further improved with the application of the 2-RC ECM-based heat generation model. Online parameter estimation using a particle-swarm algorithm with pulse discharge experiments under different ambient temperatures was employed by Pan et al. [15]. A combination of 2RC ECM and a multi-node heat transfer model based on the battery geometry was employed in the study to get a more detailed temperature gradient inside the large prismatic LIB. The research showed that the hybrid model could provide similar results to the finite element method (FEM) however, the computational burden reduced by around 90%. They also revealed that the cell geometry has a strong influence on the cell temperature profile. Despite good accuracy, the effect of cell ageing and the effort of developing pack-level thermal modelling were not considered in this study.

The impact of heat dissipation through radiation from the surface of the cell was introduced in the thermal modelling of LIB by Sun et al. [79]. A lumped thermal model considering the radiation effect was then used for core temperature estimation with the help of Extended Unscented Kalman Filter (EUKF). The sensor bias was augmented as an extended state to enhance the prediction accuracy and model robustness. While the load profile of residential energy storage was tested, the suitability in the commercial vehicle applications was not tested. Further, model parameters were assumed to be constant irrespective of environmental uncertainties which may conflict with the facts when the operating conditions will vary significantly. Zhu et al. [80] developed a lumped two-state thermal-electrical model for estimating both the surface and the core temperatures where the thermal impact of the adjacent cell was also considered during modelling. Further, an extended state observer (ESO) with the feedback of the surface temperature was employed to address the model uncertainties and time-variant parameters in the estimation model. This approach is specifically designed for rapid self-heating of self-heating batteries. The concept of model-based virtual thermal sensors (VTS) was introduced by Xiao Y.[81] that combines the tuned thermal model with KF observer along with an online parameter-identification algorithm for surface and core temperature estimation utilizing a single temperature sensor input. While the strategy is adaptive to environmental uncertainties, it still requires a sensor for feedback; thus, the strategy cannot be termed as completely sensorless. Despite, it minimizes the sensor requirement and enhanced the model adaptability the concept is similar to other lumped parameter EECM based methods. The Effect of fast-discharge on core temperature of LIB was demonstrated by Surya and Mn [14] where a combination of 1-RC ECM, single-state thermal model and KF was used for core temperate estimation. They have used a recursive least square (RLS) algorithm to identify model thermal parameters. However, further research is recommended to develop health-conscious BMS suitable for fast charging/discharging.

4.2.2. EECM-based Temperature Estimation of LIB Pack

Most of the research studies covered only the temperature estimation of a single cell. Thermal modelling and temperature estimation of LIB pack were seldomly reported. Here, a ROM of a LIB pack considering the characteristic of the inner electrical resistance of the battery was used for core temperature estimation by Ma et al. [82]. Here, RLS was used for the thermal parameter identification. In this study several assumptions were made while establishing ROM of battery pack such, parameters of each cell are the same, thermal behaviour of each cell row is same, heat transfer among cells via conduction through tabs and wires were neglected which could rise the error in temperature estimation. Thermal modelling of LIB pack by scaling-up a single cell thermal model was investigated by Ismail et al. [83] using a simulation study. Considerable accuracy has been noticed however, several assumptions were made to scale up the single-cell model to battery pack models such as uniform cell characteristics, constant ambient conditions and 100% efficient discharging process that are far from the real-life scenario. Therefore, the accuracy of the temperature estimation strategy in real-world applications needs to be further explored. Therefore, from the above discussion, it can be stated that the pack-level estimation schemes need significant further research. The EECM based temperature estimation strategies proposed by different authors are summarized in Table 2 for a quick reference to the readers. One of the major limitations of EECM-based temperature estimation techniques is the requirement of online sensor feedback. This is because the estimation accuracy is completely relying on accuracy of the knowledge of the cell thermal properties, heat generation rates, and thermal boundary conditions represented in terms of electrical parameters that are subjected to change due to cell aging, operating temperature and other practical uncertainties.

Table 2. Summary of EECM-based temperature estimation strategies.

Reference	Types of Model	Important Note

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Mahamud et al. [67]	Lumped Parameter heat capacitance-resistance thermal model	None
Forgeze et al. [39]	Lumped Parameter, Single-State, First-order model	Entropy changes
Surya et al. [66]	Lumped Parameter, Two-State, Second-order model +Kalman Filter (KF)	SOC, Surface temperature variation
Lin et al. [71]	Lumped Parameter, Two-State, Second-order model	High current rate, varying temperature, SOC
Li and Yang [72]	Extended lumped parameter, Two-state, Second-order model + Forgetting factor Recursive Least Square (FFRLS)	Temperature variation, cell ageing, SOC, Heat transfer modes
Lin et al. [41,73]	Lumped parameter, Two-state model + Least square (LS) algorithm + Non-uniform forgetting factors (NUFF)	Cell ageing and uncertainties in practical operation
Lin et al. [74]	Lumped-parameter model + Closed-loop observer	Influence of overpotential entropy changes
Sun et al. [75]	Lumped parameter, Second-order, Single state thermal model + KF	Influence of entropy changes and overpotential, surface and ambient temperature variation, charge/discharge current profile
Dai et al. [76]	Lumped parameter, Second-order, Two-state model +JKF+ LS algorithm	Initialization error and the possible time-varying external thermal resistance
Doughty et al. [77] and Park et al. [68]	Lumped parameter, Two-state model + Extended KF	Ambient temperature variation, SOC
Chen et al. [69]	Lumped parameter, Two-state thermal model + Joint KF (JKF)	Constantly varying temperature, SOC, Surface thermal resistance
Pan et al. [15]	Lumped Parameter, Second-order, multi-node model + particle-swarm algorithm	Battery geometry, charge/discharge profile
Xie et al. [78]	One-dimensional (radial) lumped parameter, Three node model + Dual KF (DKF).	Anisotropy of thermal conductivity, SOC, external temperature
Sun et al. [79]	Lumped parameter, single-state model + Extended unscented KF (EUKF)	Sensor bias, Considered heat radiation from the surface
Zhu et al. [80]	Lumped parameter, Two-state model + extended state observer (ESO)	Thermal impact of an adjacent cell, Model uncertainties and time-variant parameters
Surya and Mn [14]	Lumped parameter, Single-state thermal model + KF+ Recursive Least Square (RLS) algorithm	Effect of fast-discharge
Xiao Y.[81]	EECM based virtual thermal sensors (VTS)+ KF	Environmental uncertainties
Ma et al. [82]. and Ismail et al. [83]	ROM of a LIB pack for a central temperature of LIB pack+ Recursive least square (RLS)	Temperature, SOC

4.3. Numerical Analysis-based Temperature Estimation

Numerical analysis-based techniques try to mathematically describe the thermal dynamics inside the battery using nonlinear partial differential equations (PDEs) with complex boundary conditions, which are infinite-dimensional. Numerical methods-based techniques were successfully implemented for temperature estimation of different chemistries and shapes of LIB battery cells and even LIB packs. So far, the finite element method (FEM) [84–87] and finite volume method (FVM) [88] were extensively used for temperature estimation. Dong Hyup Jeon [84] incorporated a transient thermo-electric model with a porous electrode model and conducted a numerical simulation to understand the thermal behaviour of commercial LIB under charging and discharging conditions. He demonstrated that temperature increase during discharging is much higher compared to the temperature rise during charging. He also suggested that the temperature difference between

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charge and discharge can be decreased with increasing C-rates. Further, Baba et al. [85] conducted a numerical simulation of an enhanced single-particle model of LIB to understand the three-dimensional temperature distribution inside the cell. Similar FEM analysis with a three-dimensional model and Bernardi equation-based internal heat generation rate was conducted by Du et al. [86]. Numerical analysis was used for transient behaviours of a LIB under a dynamic driving cycle by Yi et al. [87]. Double-layer thermal capacitance was used to capture the short-term transient behaviour of the LIB chemistry. Fleckenstein et al. [88] using FVM to demonstrate that the temperature gradients inside the cell layer result in different current densities and local SOC inhomogeneities in LIB. These phenomena must be well-taken care of while designing an effective thermal management system. In general, this kind of model is best for capturing both temporally and spatially thermal distribution of the cell as the battery thermal process is a typical distributed parameter system. Despite high accuracy, detailed information about cell temperature gradient these numerical method-based temperature estimation strategies are not suitable for online temperature estimation due to high computational cost. The complex mathematical analysis also required expertise and strong domain knowledge. Moreover, generalization is not possible as different chemistry and cell physics affect mathematical modelling. A summary of numerical methods-based temperature estimation strategies is shown in Table 3.

Table 3. Summary of numerical methods-based temperature estimation strategies.

Reference	Types of Model	Important Note
Dong Hyup Jeon [84]	A transient thermo-electric model with a porous electrode model + finite element method (FEM)	Different driving cycles
Baba et al. [85]	Enhanced single-particle model +FEM	Three-dimensional temperature distribution inside the cell, Cell geometry, and current profile
Du et al. [86].	Three-dimensional model + ECM based heat generation model +FEM	Different current profile, Temperature variation
Yi et al. [87].	Transient thermo-electric model +FEM	Transient behaviours under dynamic driving cycle
Fleckenstein et al. [88]	Three-dimensional model + FVM	Different current density and local SOC inhomogeneities at different cell layer

4.4. Direct Impedance Measurement-based Temperature Estimation

Cell internal temperature estimation using a lumped-parameter thermal model and an approximate distributed thermal model have several drawbacks. Firstly, accurate determination of thermal model parameters such as heat generation and cell thermal properties is highly challenging. Heat generation inside the cell is typically approximated by measuring the cell operating current, voltage and the internal resistance that are again the functions of SOC, cell internal temperature and SOH. Moreover, a cell is constructed using many different materials combined into a layered structure and thermal contact resistances between these layers are often unknown. Temperature estimation methods use surface temperature measurement and even the combination of surface-mounted temperature sensor and thermal model typically failed to detect the thermal runaway as rapid fluctuations in internal temperature is difficult to capture using surface mounted sensor because the heat conduction between the core and battery surface takes a considerable amount of time [89]. Furthermore, embedding micro-temperature sensors within the cell [90,91] is not practically possible for a large capacity LIB pack from a manufacturing complexity and system cost point of view. Hence, the core temperature measurement using a physical sensor is not an appropriate method for industrial applications.

Srinivasan et al. [92,93] noticed that the phase of electro-chemical impedance in the frequency range of 40 and 100 Hz is temperature-sensitive but insensitive to changes in other parameters such as SOC and SOH. Based on these findings, they have demonstrated an electro-chemical impedance-based cell internal temperature estimation strategy. However, they have assumed the uniform internal temperature and the estimation method is only valid in the temperature range of -20 to 66 °C. The temperature estimation considering the effect of temperature non-uniformity on electrochemical impedance was studied by Schmidt et al. [94] based on the principle derived by Troxler et al. [95]. Both the strategy developed by Srinivasan et al. and Schmidt et al. were only able to estimate the mean temperature of the cell, however in real-life application especially in the case of cylindrical battery under high charging/discharging current the difference between internal maximum temperature, surface temperature and mean temperature are significantly high. Therefore Richardson et al. [3] further extended the research and developed a thermal-impedance model by combining an EIS measurement at a single frequency with a surface temperature measurement for precise determination of internal temperature distribution. This approach does not require knowledge of cell thermal properties, heat generation or thermal boundary conditions however the major limitation is the online impedance determination of each cell which is highly challenging. Moreover, uncertainties of environmental factors were not considered and surface mounted temperature sensor needs to be installed on each cell which is impractical so far. Whilst few approaches of online determination of impedance spectra across multiple frequencies using onboard power electronics of EVs have been reported [96], the application of these strategies in real-time temperature estimation has not yet been investigated. Furthermore, interpreting impedance measurements under super-imposed DC currents is yet to be systematically investigated.

Online EIS-based temperature estimation strategy termed impedance-temperature detection (ITD) was proposed by Richardson and Howey [97] for sensorless temperature estimation which is adaptive to cell ageing and practical uncertainties. However, ITD cannot provide a general solution alone, thus such strategy combine surface mounted sensor with ITD for accurate online temperature estimation [3]. Still, temperature sensors are required to be installed. Further to this study, they have integrated ITD with an electric-thermal model along with a DEKF for online core temperature estimation of LIB cell even with unknown convection coefficient. They have also demonstrated that the performance of the thermal model plus ITD is almost similar to the ITD with surface thermal sensors. Despite the advantages, the major limitations of the strategy are, online impedance determination and the requirement of an accurate electric thermal model thus encompasses the same drawback of conventional thermal modelling bases strategies. Moreover, although the strategy can estimate both core and surface temperature of an individual cell, however, pack level estimation strategy was not illustrated in this study.

The influence of cell temperature, SOC and SOH on the impedance spectrum, excitation frequency and thereby estimation accuracy of cell internal temperature was investigated by Zhu et al. [98]. Here, the temperature estimation was made based on an impedance response matrix analysis which was developed using EIS measurements. Despite high accuracy, the effect of the non-uniformity of the cell temperature and the correction method was not considered. Moreover, an extensive experimental study is required for modelling and the computational cost is also very high. Thus, the online application of the strategy is challenging. Identification of suitable frequency and other EIS parameters is very difficult whilst the estimation accuracy significantly dependents on these parameters. Moreover, accurate determination of the real and imaginary parts of the impedance is highly challenging, whilst different decisions for these two parts lead to inaccurate temperature estimation. A combination of Linear Parameter Varying (LPV) thermal model and a polytopic observer-based battery cell temperature estimation algorithm was proposed Debert et al. [99]. The EIS-based strategy was also employed in references [3,100–103] to estimate the core temperature. Despite high accuracy, the major limitation is the determination of accurate impedance-temperature characteristics and it should be acquired in advance through tedious preliminary tests. In addition, the impedance-temperature characteristic of a cell is influenced by cell ageing leading to inaccurate prediction due to SOH deterioration.

Table 4. Summary of direct impedance measurement-based strategies.

Reference	Types of Model	Important Note

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Srinivasan et al. [92,93]	Direct measurement of electro-chemical impedance	None
Schmidt et al. [94]	Direct measurement of electro-chemical impedance	Temperature non-uniformity
Richardson et al. [3]	Thermal-impedance model + EIS measurement at single frequency+ surface temperature feedback	Independent of cell thermal properties, heat generation or thermal boundary conditions
Richardson and Howey [97]	Online EIS measurement (impedance-temperature detection (ITD) + dual-extended Kalman filter (DEKF)	Unknown convection coefficient
Zhu et al. [98].	Impedance response matrix analysis, developed using EIS measurements	Influence of cell temperature, SOC and SOH on the impedance spectrum

4.5. Machine Learning-Based Temperature Estimation

With the overwhelming complexity of the electro-chemical reactions inside the battery and the sensitivity of the battery parameters to the uncertainties of the working environment, the thermo-dynamic behaviour varies significantly from the center region to the surface region. Most of the existing distributed thermal models and the lumped parameter thermal models are incapable to consider the spatiotemporal distribution of LIB packs especially in the case of large-capacity battery packs. Moreover, it is highly difficult to represent these spatiotemporal dynamics by a single physics-based model. Here, the machine learning (ML) algorithms were widely employed to preserve the local dynamics to improve the modelling accuracy of nonlinear systems like LIB. Regarding this, Liu and Li [104] employed a hybrid model of EECM and neural network (NN)-based learning approach to develop a spatiotemporal thermodynamic model of LIB for accurate estimation of internal temperature distribution. The data-driven NN model used commonly measured signals of BMS to compensate for the model-plant mismatch caused by spatial nonlinearity and other model uncertainties.

NN and support vector machine (SVM)-based [105] LIB temperature estimation strategy was investigated by Sbarufatti et al. [106]. A hybrid model of RBF neural network (RBFNN) and EKF was employed by Liu et al. [107] to estimate the internal temperature of LIB. While they have considered the impact of temperature on cell behaviour, the primary intention of these models was the estimation of SOC or SOH rather than estimating cell temperature. One of the major challenges of pure ML-based strategies is the generalization capability. Feng et al. [108] developed an effective electrochemical-thermal-neural-network (ETNN) by fusing a lumped parameter electrochemical thermal, feed-forward neural network (FFNN) and a UKF. This method demonstrated appreciable performance in predicting the state of temperature (SOT) in a wide temperature range and large current conditions. However, the modelling is highly complex, the accuracy over different charging current/drive cycles was not tested. Moreover, the computational efficiency and the suitability for online application are questionable. The back of the ETNN is the electrochemical model thus encompasses the similar drawbacks of electro-chemical models. In general, while ML-based schemes are computationally efficient, however, collecting data training data and the model training procedures are highly complex and time expensive. Moreover, real-life battery test data was not considered during ML-based model training in the existing literature, therefore the accuracy of the existing ML-based strategies is still questionable. A summary of ML-based techniques reported by researchers are presented in Table 5.

Table 5. Summary of ML-based temperature estimation techniques.

Reference	Types of Model	Important Note
Liu and Li [104]	EECM + neural network (NN)-based learning approach	Model-plant mismatch caused by spatial nonlinearity and other model uncertainties
Sbarufatti et al. [106].	Neural networks + Support vector machines	Influence of temperature, charging/discharging current

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Liu et al. [107]	RBF neural network (RBNN) and the extended Kalman filter (EKF)	Impact of temperature on cell behaviour
Feng et al. [108]	Electrochemical-thermal-neural-network (ETNN) + Unscented Kalman filter (UKF).	Wide temperature and large current conditions

4.6. Magnetic Nanoparticles-based Temperature Estimation

The magnetization of Magnetic Nanoparticles (MNPs) is nonlinear under an ac magnetic field and the accurate temperature of MNPs could be estimated by using the ratio of the third and fifth harmonic response [109–111]. Further, the temperature sensitivity of MNPs with the increased DC magnetic field was studied by Zhong et al. [112]. They found that the temperature sensitivity of MNPs will decrease with an increased DC magnetic field. Further to this study, Zou et al. [113] developed an improved Magnetic nanoparticles thermometer (MNPT) for the core temperature estimation of LIB which works based on the temperature measurement of magnetic nanoparticles (MNPs). They have also suggested the optimal range of the DC magnetic field strength to ensure maximum temperature sensitivity and minimum temperature error of the MNPT. It is noticed that this type of estimation topology is very bulky and costly. Moreover, the suitability of online prediction has not yet been assessed.

5. Discussion on Issues, Challenges and Future Research Recommendations

Temperature estimation schemes for LIBs can be designed with different levels of complexity depending on the requirement of accuracy level and detailing of the prediction results. Detailed model results in more accurate prediction which is essential for more safe and reliable operation of BMS. However, integrating more detailed cell phenomena into the model eventually increases the modelling complexity, computational cost while at the same time reduce the suitability for online prediction and low-cost on-board BMS. For instance, modelling complexity increases if the temperature gradient of each cell layer is considered instead of concentrated heat generation at the core. Secondly, the heat fluxes inside and outside the battery can be considered in both axial and radial directions instead of considering the only radial direction for simplicity. Furthermore, detailed models typically consider different heat transport modes, that is, conduction, convective and radiation whereas simplified models consider only conduction heat transfer. Integrating a greater number of phenomena in thermal modelling requires a lot of parameters, resulting in additional requirements of experimental measurements, modelling time and solid domain knowledge. In addition, very detailed and accurate information of cell structure, material properties and cell assembly are also needed. However, collecting this information from cell manufacturer are highly challenging due to the confidentiality of the design data. Therefore, it can be inferred from the above discussion that the detailed models could produce highly accurate and complete insight into cell thermo-dynamics, however, their computational complexity may not be suitable for online prediction and on-board low-cost BMS. In general, most of the estimation strategies require measurements from physical sensors, however installing a physical sensor at each cell is not practically possible as a high capacity LIB pack consists of thousands of individual cells. Moreover, installing a sensor at the cell core for core temperature measurement is highly challenging. Several estimation schemes estimate core temperature based on the surface temperature measurement. However, it is very erroneous as it took a significant amount of time to reach the heat to surface from the core. So far most of the research studies covered the temperature estimation scheme of a single LIB cell. Temperature estimation of LIB pack is much more challenging. Thus, significant further research is recommended here. Moreover, the influence of fast charging/discharging on the cell temperature has not yet been deeply explored. This is highly recommended to develop a health-conscious BMS. A summary of existing issues, challenges and future research recommendations to the research community are presented in Table 6.

Table 6. Summary of major issues, challenges and research recommendations.

Strategy	Major Issues and Challenges	Future Research Recommendations
Electro-chemical Model-based	• Extremely detailed modelling is possible. Thus, it could produce a highly accurate prediction, however with the expenses of very high computational cost. Thus, unsuitable for online prediction by onboard BMS • In-depth prior knowledge of LIB chemistry is a must besides expertise in mathematical modelling, resulting in dependence on domain experts • Extensive experiments are required to accumulate detailed information on battery characteristics • Modelling is highly complex • Developing an adaptive estimation scheme is highly challenging • Poor generalization capability	• Significant future research is recommended to reduce modelling complexity and computational cost. • So far, it can produce the best prediction results, thus could be extensively used for the validation of other types of models and data acquisition for data-driven models LIB chemistry is highly sensitive to temperature, battery health and other uncertainties thus further research on adaptive modelling is recommended
Equivalent Electric Circuit (EECM) Model-based	• Most extensively used so far due to adequate accuracy and easy implementation, however modelling complexity and computational cost increases with the order of model, number of temperature measurement points (nodes) and the parameter distribution • Accurate EECM parameters are very difficult to identify, especially online parameter estimation • Parameter tuning using external measurement is challenging and time expensive • Few researchers also used electro-chemical analysis for parameter identification and determination which possesses similar difficulties to electro-chemical-based strategies • Predictions are highly influenced by measurement noises and often too many physical sensors are required • Lower order models/simplified models are so far extensively used for online prediction with the compromise of accuracy and detailed insight	• Modelling complexity and Computational cost can be controlled by treading-off between accuracy requirement and detailing of the model. • Adaptive parameterization is challenging, however with the fusion of advanced algorithms such as ML-based techniques, adaptive strategies could be developed. • These models can generate highly accurate results at the laboratory thus could be used to generate data and model validation of other strategies • Fusion of this strategy with other strategies such as ML-based techniques could produce enhance accuracy and computational performance • Instead of traditional filters, more advanced adaptive filtering techniques could be embedded for better performance
Machine Learning (ML)-based	• Completely data-driven black-box strategy, that is, prediction depends on the external measurements only, thus minimal or no requirement of any domain-specific knowledge, however, the major challenge is the accumulation of high-quality large volume of training data. • No requirement of iterative complex mathematical calculation thus computational cost is adequate for online application, however computational cost increases with the high volume (high resolution) data and number of feature vectors to get a better insight • Accumulation of high-resolution data especially manufacturer data and fault data are highly challenging. These data are important for accurate and adaptive prediction • Generalization is challenging • Currently not used on onboard BMS due to high training time and complex algorithm development and computational time, whilst it is noticed very few efforts have been made so far • Often, external measurements by physical sensors are required as feedback for online parameter adjustment thus still requires to install of physical sensors	• While it is comparatively easy to develop adaptive models, however, very few efforts have been made so far. • Cell characteristics are highly influenced by temperature, ageing and other uncertainties thus further research on adaptive modelling is recommended • Generalization is difficult, however, with the incorporation of advanced adaptive algorithms it could be possible • With proper design efforts, it could be used for online prediction and implement in onboard BMS with low processing power • Very promising technology could be used for future generation sensorless temperature estimation strategies. Very little effort has so far provided, thus further research is recommended

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Numerical Model-based	• These strategies use FEA and FVA. FEA and FVA based temperature estimation strategies are considered the most accurate and most computationally expensive. • Due to iterative complex mathematical calculation, its computational cost is very high, thus not suitable for online prediction	• Significant research and development are required to improve computational cost to make this suitable for online prediction As it is most accurate thus could be used for other model validation and accurate data collection
Direct Impedance Measurement-based	• The influence of temperature on cell impedance is used for internal temperature estimation. However, online direct measurement of impedance using onboard power electronics is highly challenging • Changes in cell impedance due to temperature variation is small, thus accurate determination of such small changes is highly difficult • Existing schemes are very bulky Very few research efforts have so far provided, not yet practically implemented	• Promising technology thus significant further research and development is recommended to reduce scheme size and assess the practical applicability in onboard BMS • Accuracy in real-world applications need to be judged • Further research on online impedance determination using onboard electronics is also recommended. • Cost of existing solutions is very high, which need to be addressed
Magnetic Nanoparticle-based	• Very new technology, it is too early to comment	• Practical applicability in on-board low-cost BMS has not yet been investigated. Overall, significant further research is required

6. Conclusions

This article presented a comprehensive review of the state-of-the-art temperature estimation strategies for lithium-ion batteries (LIBs) covering the necessity of an optimum estimation strategy, detailed discussion on the existing strategies, current issues, challenges and future research recommendations. It can be inferred that an accurate temperature estimation of LIBs is indispensable for effective thermal management, operational safety and several other crucial tasks of a Battery Management System (BMS). Measurement of each cell temperature using physical sensors is not practically possible, especially for high capacity battery pack consists of thousands of individual cells. To develop an ideal temperature estimation scheme, one needs to concentrate on several factors, such as high accuracy, adaptability, small in size, real-time estimation, distributed (to monitor the temperature gradient of the entire cell), low cost, and easily implementable for wide adoption. Typically, a temperature estimation scheme consists of a heat generation model and a heat transfer model. Depending on the modelling and computation strategies temperature estimation schemes can be grouped into six categories namely, electro-chemical model-based, equivalent electric circuit model (EECM)-based, machine learning (ML)-based, numerical analysis-based, direct impedance measurement-based, and magnetic nanoparticle-based. So far, numerical analysis-based schemes are most accurate followed by electro-chemical model-based schemes. However, both the strategies have very high computational cost making inappropriate for online prediction by a low cost on broad BMS. Moreover, modelling complexity and experimental requirements are very high alongside the necessity of domain-specific knowledge. EECM-based schemes can be designed with different levels of complexity, accuracy level and computational cost. Simplified lower-order EECM-based schemes are extensively used in literature and practice. Machine learning (ML)-based schemes are very promising due to their higher level of accuracy, ease of implementation and adaptability. In addition reduced or even no requirement of equivalent modeling and domain experts. However, to obtain the feature vectors, very large volume and high quality data is required which are typically very challenging to acquire. Here, a hybrid strategy combining an EECM and an ML presumably a suitable solution. Direct impedance measurement and magnetic nanoparticle-based schemes are very newly developed. It is too early to assess their capability and suitability for online prediction and implementation in onboard BMS. Therefore, systematic guidelines about open research areas and future research directions are highlighted in this study. It is also noticed that the majority of the research studies proposed temperature estimation schemes of a single LIB cell whereas temperature estimation of LIB pack is much more challenging. Thus, significant further research is recommended here a well.

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