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Temperature-Dependence in Battery Management Systems for Electric Vehicles: Challenges, Criteria, and Solutions

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ABSTRACT Owing to a global effort towards reducing carbon emissions, electric vehicles (EVs) have emerged to replace the petroleum-fueled vehicles. However, the battery is a bottleneck restricting EVs from being utilized in the same way as petroleum-fueled vehicles. Lithium-ion batteries (LiBs) are commonly used in EVs, but have an optimal temperature range, and operation outside this range causes accelerated aging in the form of capacity fading and power fading, especially in cold climates. We propose that both state parameter estimation and thermal management are interconnected problems and should be addressed together: Battery health and performance depends on temperature, while temperature depends on operational conditions, battery health, structural design and thermal management. Temperature dependent decay accounting for heat generation in cells, temperature variation between cells and heat transfer with surroundings, can allow more accurate state parameter estimation and guide thermal management strategies. This review investigates how the dynamics of temperature dependence and heat generation are addressed in the literature related to estimation of battery state parameters. Approaches involving temperature were divided into three categories: 1) maintain constant ambient temperature and omit battery temperature, 2) verify at different ambient temperatures, and 3) use available data for cell and/or ambient temperature. A valid solution to the problem in real applications, must satisfy three criteria: a) suitable for online applications, b) scalable to battery packs, and c) applicable to dynamic battery cycling occurring during normal use. The most promising methods include coupled thermal and electric models with adaptive filtering, and recurrent neural network methods.

INDEX TERMS Adaptive filters, battery management systems, equivalent circuits, machine learning, state estimation.

I. INTRODUCTION

In a global effort towards climate consciousness in recent years, many governments have defined goals for reducing

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carbon emissions in the 2025-2035 period [1], such as moving towards zero-emission transportation [2]. Electric vehicles (EVs) have an important role in this process. Even though EVs have a potential for low emission operation when using a clean electricity source, batteries are responsible for a considerable part of the manufacturing phase emissions [3], [4].

TABLE 1. Battery state estimation reviews.

Authors	Year	Parameters	Description
Si et al. [9]	2011	RUL	Statistical data driven approaches, directly and indirectly observed state processes
Watrín et al. [10]	2012	SoC, SoH	Adaptive systems: Kalman filter, Artificial neural network, Fuzzy logic systems
Lu et al. [11]	2013	SoC, SoH, SoF	Key issues, state estimation and fault diagnosis
Rezvanizani et al. [12]	2014	SoC, SoH, SoF	Battery prognostics and health management
Farmann et al. [13]	2015	SoC, SoH, SoF	Electromotive force, electrochemical, incremental capacity analysis, differential voltage and aging prediction-based models
Farmann et al. [14]	2016	SoAP	Adaptive models, fuzzy logic, machine learning, equivalent circuit models
Berecibar et al. [15]	2016	SoH	Experimental techniques, adaptive models, degradation mechanisms
Wang et al. [8]	2016		Thermal management models and solutions
Tao et al. [16]	2017	SoC, SoH, SoF, RUL	Stochastic models
Hannan et al. [17]	2017	SoC	Experimental methods, adaptive filters, data-driven methods, non-linear observers
Liu et al. [18]	2017		Thermal models, electrochemical models, equivalent circuit models, thermal management system
Xia et al. [19]	2017		Thermal management of battery thermal response at module level and cell level
Xiong et al. [20]	2018	SoC	Look-up-table based methods, Coulomb counting, model-based method, Data-driven methods
Xiong et al. [21]	2018	SoH	Experimental and model-based estimation methods
Lipu et al. [22]	2018	SoH, RUL	Direct, adaptive, data-driven, stochastic methods

Despite technological progress, batteries still restrict EVs from being utilized in the same way as petroleum-fueled vehicles (PVs) and improvements to the management of battery health can facilitate improved performance and emission reduction by less frequent battery replacement.

Lithium-ion battery (LiB) technology is one of the most popular battery technologies for EVs [5], [6]. However, thermal management challenges inhibit LiB performance, health and safety. High temperature operation reduces lithium inventory resulting in capacity fade, while low temperatures reduce the amount of active anode material resulting in capacity and power fade [7], both degrading the battery at accelerated rates. Furthermore, operation at high temperatures can initiate destructive processes causing permanent damage to battery components or vehicle, such as swelling, fire and explosion [5].

This review was motivated by work related to thermal management in EV battery packs. To address effective and economic battery thermal management solutions, it is necessary to consider the thermodynamics within a battery pack and temperature dependence on health and performance, especially considering non-uniform accelerated aging of battery cells from temperature variation between cells. Recent literature, covered in this review acknowledge the importance of temperature, but tend to constrain the operating conditions to a limited set of fixed ambient temperatures, within the optimal temperature range for the battery [8]. In addition, the cell surface/core temperature changes dynamically depending on health and charge/discharge rates and may vary between cells [5]. A viable solution needs to take temperature into consideration but must also possess the following characteristics: 1) suitable for online battery monitoring, 2) scalable to battery packs, and 3) compatible with dynamic cycling.

Several reviews in recent years have focused on methods for estimating battery state parameters such as SoC (State of Charge), SoH (State of Health), RUL (Remaining Useful

Life), State of Function (SoF), State of Available Power (SoAP), see Table 1.

This review attempts to provide a critical overview on how battery monitoring methods address dynamic temperature variation in battery packs, which can be important for: challenges in cold climates [23], high temperature safety issues [5] and general longevity and performance [7]. The focus is on recent literature, published starting from 2016, gathered primarily from Science Direct and IEEE Xplore, with combinations of keywords, such as: battery, management systems, state estimation, temperature dependence, thermal management.

II. BATTERY STATE ESTIMATION METHODS

Battery state estimation methods are used to describe the internal battery state, which is necessary to operate a battery powered system effectively, sustainably and safely, given the nonlinear behavior of the electrochemical reactions and dependence on operating conditions. Defined state parameters generally describe three properties of the battery: Amount of stored charge, decay of maximum capacity compared to a new battery, and amount of power the battery can deliver, most commonly described by SoC, SoH, SoF respectively, or alternatives. A brief introduction to typical methods has been arranged in three categories: experimental methods, model-based methods and data-driven methods.

A. EXPERIMENTAL METHODS

Experimental methods as defined here are methods that explore battery properties with non-destructive experimental procedures.

Coulomb-counting estimates the amount of charge in the battery by integrating the current transferred to or from the battery over time, to determine the remaining charge relative to the maximum charge (SoC), or maximum capacity relative to nominal capacity (SoH) i.e. fading of maximum

TABLE 2. ECM recommendations.

Work	Optimization	Battery type	Recommended ECM
He <i>et al.</i> 2011 [35]	Initial Regression + (unspecified) genetic algorithm	LiMn ₂ O ₄	2RC
Hu <i>et al.</i> 2012 [37]	Multi-particle swarm optimization	LiNMC LiFePO ₄	1RC 1RC-H
Westerhoff <i>et al.</i> 2016 [36]	Initial Regression + trust-region/Levenberg-Marquardt non-linear regression	LiN _{1/3} Mn _{1/3} Co _{1/3} O ₂	For EV: ≥ 3RC or 1RCPE
Lai <i>et al.</i> 2019 [38]	Nonlinear programming, physics-, evolution- and (6) swarm-based methods	LiNMC	≥ 2RC-H is <i>not</i> suited for online

capacity compared to a new battery [21]. This method is appropriate for online applications, but suffers from inaccuracies due to sensor error accumulation and initial value error. However, Coulomb-counting is often used in combination with model-based methods due to its relatively simple implementation [24].

Hybrid Pulse Power Characterisation (HPPC) tests and Electrochemical Impedance Spectroscopy (EIS) are methods used for nondestructive characterization of electrical response in a chemical system. HPPC tests are performed by monitoring voltage changes during short high current charge/discharge pulses with relaxation periods. The cell voltage response is affected by electrochemical kinetics of the battery, such as ohmic losses, double layer capacity and lithium ion diffusion [25], [26]. EIS measures the current and voltage relationship over a frequency range [25], and can be used to model kinetic battery processes through the impedance spectrum and estimate physical properties like diffusion coefficients and reaction rates. EIS requires linearity, stability and causality making it challenging to implement as an online method [27]. Since the battery impedance is dependent on temperature; HPPC and EIS can be performed at different ambient temperatures with very different results [28], [29].

Incremental Capacity Analysis (ICA) and Differential Voltage Analysis (DVA), measures the change in charge (Q) and cell voltage (V) in a cell at equilibrium during charging/discharging as the gradients dQ/dV and dV/dQ respectively, to determine changes in electrochemical properties [30]. Different degradation modes can be identified by defining feature points (such as peaks or plateaus) from IC and DV curves and observing the change during aging. Challenges for ICA/DVA analysis in online applications includes differentiation of discrete noisy data, the assumption of equilibrium conditions, and establishing the IC-DV curves when the driving conditions determines the discharge process [30], [31].

The experimental methods alone are most suitable for offline SoH determination due to the required experimental conditions, such as full cycles, constant temperature and a disconnected battery, although attempts have been made to achieve online functionality such as online static charging SoH identification with partial ICA charging data [32], or online EIS for fuel cell EVs [33]. Experimental methods are commonly used in combination with model-based methods such as HPPC for model parameter determination [34].

B. MODEL-BASED METHODS

The model-based approach is based on using an approximate equivalent model to represent battery dynamics, with adaptive filtering of available sensor data for estimation of unobservable state parameters.

1) EQUIVALENT CIRCUIT MODELS

Equivalent circuit models (ECMs) for LiB cells are used in battery state estimation to describe the Voltage-Current characteristics of the battery. ECMs can be designed with different objectives like accuracy, parameter estimation computational load and reliability, where model parameters can be determined by experimental procedures and optimization methods. There is no definite answer for selecting the most appropriate ECM given a battery technology, type and application. Different studies recommend different models [35]–[38], see Table 2 and suggested ECMs in Figure 1 (Figure 1a generalized for different number of RC parallels and optional Hysteresis voltage). The impact of optimization method on computational load was only considered by Lai *et al.* [38]. This demonstrates that results and recommendations from different studies that address computational load are not directly comparable if they use different optimization methods. However, considering the application and trade-off between accuracy, performance and reliability, the simple models are generally preferred. The 1RC [39]–[46], and 2RC [34], [47], [48] are commonly used ECMs.

2) ADAPTIVE FILTERS

Adaptive filters such as variations of Kalman filters (KF) [44], [49]–[51] and Particle filters (PF, also called Sequential Monte Carlo) [44], [46], [49], [52] are commonly used for battery state parameter estimation. Adaptive filtering is based on a prediction step where the state estimate and error is projected ahead according to the model, and a correction/update step to correct the prediction by comparing predictions to measurements. Adaptive filters can estimate unobservable states in dynamic systems based on a dynamic model and output measurements formulated as state-space equations (1) and (2):

$$x_k = f(x_{k-1}, u_k) + w_k \quad (1)$$

$$z_k = h(x_k) + v_k \quad (2)$$

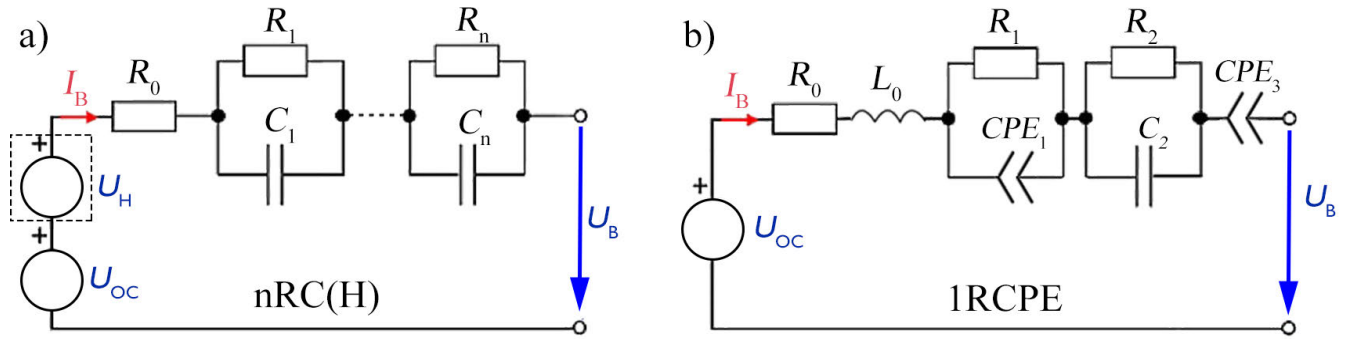


FIGURE 1. ECMs from Table 2: a) n^{th} -order RC ECM with optional Hysteresis Voltage (U_H) [37], [38], b) 1RCPE ECM, incorporating Constant Phase Elements (CPE) [36].

x_k is the unobserved state, z_k is the output (measurement), u_k is control input, w_k , and v_k are process and measurement noise and $f(\cdot)$ and $h(\cdot)$ are state transition and observation models.

Standard KF relies on f and h being linear functions of the state, so modifications such as Extended-KF and Unscented-KF was developed to handle nonlinear models. If the model is inaccurate or not well known, PF is often used, but PF is Monte Carlo based and more computationally intensive and may be more challenging to implement in online applications. Adaptive filters can take advantage of both a dynamic model and sensor measurements, in the presence of process and measurement noise, and obtain more accurate results compared to either models or measurements alone [53], [54].

The battery ECM can be formulated as differential equations and discretized [55] to (1) and (2) and is therefore appropriate for adaptive filtering to estimate the unobservable state variables of batteries. The introduction of temperature in addition to e.g. current and voltage in the state-space model requires an energy balance equation to couple the ECM with the thermal domain.

A general battery energy balance was proposed by Bernardi *et al.* [56], accounting for: Reactions, change in system heat capacity, phase change, mixing, electrical work and heat transfer with surroundings under the assumption of uniform battery temperature. In the context of battery health monitoring, an assumption of uniform battery temperature may be unreasonable, depending on thermal management strategy and battery type, since accelerated decay have been demonstrated for surface cooling of cylindrical cells. Heat generation occurs primarily in the core, and surface cooling increases the temperature gradient in the battery cell causing accelerated decay [57], [58]. In an isolated cell the contributions from irreversible heat (joule heating) and reversible heat (entropy change) dominates the battery heat generation, but additional terms can be included to increase accuracy at the cost of increased model complexity [56], [59]. For application in a pack of cells with a thermal management strategy, it is also necessary to consider heat transfer with surroundings, such as coolant fluid, ambient air, battery casing and other

cells (3).

$$m c_p \frac{\partial T}{\partial t} = \underbrace{I_B (U_{OC} - U_B)}_{\text{Irreversible}} - \underbrace{I_B T \frac{\partial U_{OC}}{\partial T}}_{\text{Reversible}} + \underbrace{q}_{\text{surroundings}} \quad (3)$$

Non-uniform cell temperature can be incorporated by establishing a thermal resistance lumped model for cells with surface/core/average temperature [48].

C. DATA-DRIVEN METHODS

Data-driven methods are generally model-free black-box methods that can give rapid and accurate results given sufficient training data. In a practical commercial application, comprehensive failure data for training is challenging to obtain before new products or battery technologies enter the market. The difference in battery dynamics among battery types makes direct reuse of trained models difficult. Generation of sufficient training data is important, but challenging if changes to battery pack configuration, design, cell chemistry etc. can make existing training data nonrepresentative, warranting collection of new representative training data. There may also be challenges with over- or underfitting: Is the training data representative of all relevant scenarios, or are there situations that will produce complete failure of the model? However, as pointed out by You *et al.* [60] the model-based methods and experimental methods for SoH often rely on constrained assumptions such as full cycling with constant current, which is not representative of partial and dynamic cycling that can be expected during real life operation.

III. CRITERIA FOR TEMPERATURE-DEPENDENT METHODS

The reviewed battery monitoring methods address temperature according to the following 3 categories:

- 1) Maintain a fixed ambient temperature, omit temperature dependence or heat generation in the battery.
- 2) Assume temperature dependence of model parameters, update model parameters periodically. An extension of 1) by either validating for a range of temperatures, or update the model parameters when battery temperature drifts too far.

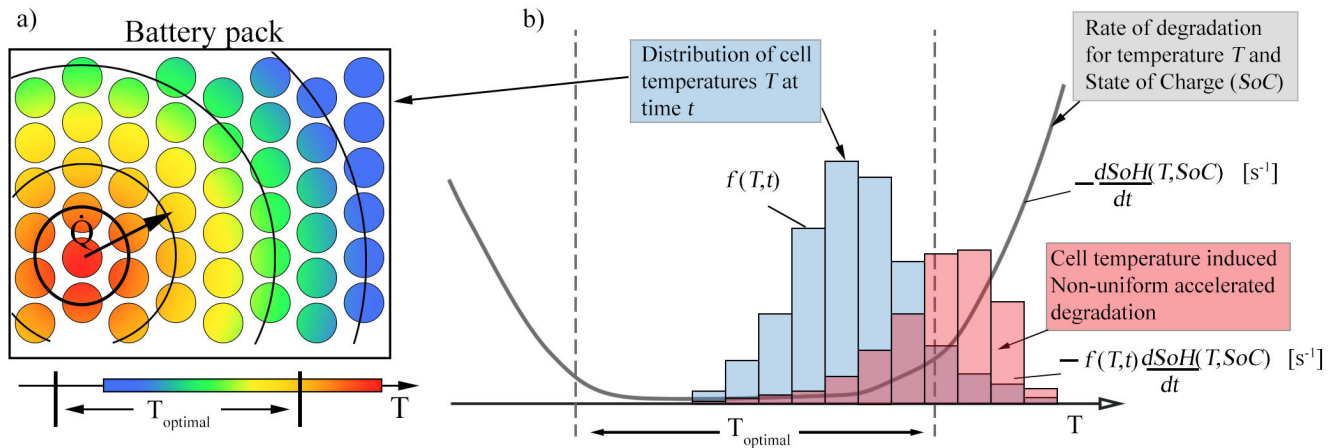


FIGURE 2. Conceptual figure. a) Visualization of temperature distribution in a battery pack, b) distribution of cell temperature T at time t (shaded blue histogram), rate of degradation ($dSoH/dt$) with respect to time for different temperatures, and the product of the two (shaded red) showing effective accelerated ageing at different temperatures.

- 3) Use available sensor data as it becomes available (e.g. temperature, voltage, current). Update model for real-time temperature data, and/or temperature data for the present cycle or historical charge/discharge cycle data

The following criteria (A-C) were defined as constraints for a method to serve as a viable solution to the problem at hand.

A. ONLINE PREDICTION

The method must be suitable for integration with battery management systems, with functionality for real-time or near real-time predictions of SoC/SoH or other state parameters while driving. The method therefore needs to be non-destructive, rapid, accurate and with manageable computational intensiveness.

Compromises are possible during the stationary charging process. More intensive diagnostic procedures suitable for offline use can be applied for a stationary shut-down vehicle compared to during normal operation, such as measurements over a full/partial charge cycle for a disconnected battery.

B. BATTERY PACK

Extending from a single cell to battery pack complicates the issue, as it requires scaling to an application-dependent number of cells, with design dependent interaction between cells. It is possible to connect one ECM per cell, but depending on the number of cells, the complexity of the model can involve optimization of a large number of parameters, which can be computationally intensive depending on the optimization method, and require more measurements/training data. On the other hand, if the set of connected cells is considered as a single equivalent model, the number of parameters is manageable, but it will not be able to capture inter-cell variation. New cells with the same chemistry exhibit similar behavior [37]. However, variations in fabrication processes,

design of battery pack, thermal management may apply a different set of conditions to different cells causing subsets of cells to be cycled at more extreme temperatures than others, leading to a temperature-induced non-uniform accelerated aging (see Figure 2). Rate of decay depends on temperature and aged batteries produce more heat (see Figure 3d), which can be transferred to adjacent cells and further accelerate decay. The heat generation within cells, heat transfer between cells and with surroundings, and how this relates to SoH should be taken into account when considering strategies for thermal management and equalization of cells with different SoH and SoC.

C. DYNAMIC PROFILES

The electrochemical processes in the battery cells depend on temperature, and the temperature of the battery cells will vary according to energy conservation (3) [56] even with constant ambient temperature. Furthermore, cell temperature has been successfully demonstrated as predictors for SoC, SoH and SoP [48], [60], [61]. In real applications the conditions are not ideal and mostly unknown ahead of time, e.g. varying ambient temperature and partial discharge of battery pack based on trip distance, traffic and road conditions.

The literature has been summarized in Table 3, categorized according to the temperature approach (1-3) and constraints (A, B, C).

IV. DISCUSSION

In online applications and real scenarios, temperature approach 1 and 2 suffer from the implicit assumption that ambient temperature is a proxy for battery temperature, and that the battery can be operated in equilibrium under fixed conditions. The battery dataset from the NASA Ames Prognostics Center of Excellence is often used to test developed battery state estimation methods (see Table 3) with such conditions [72]. The NASA data set contains data from fairly

TABLE 3. Recent literature on battery state estimation.

Work	Method	Parameter	A	B	C	Battery
Temperature approach 1						
Duong <i>et al.</i> 2018 [49]	HKF – PF – R	RUL	-	-	-	*NASA
Yang <i>et al.</i> 2018 [39]	ECM – R	SoH	X	-	-	2.5Ah LiFePO ₄ batteries
Yu <i>et al.</i> 2017 [52]	PF – R	SoH	X	-	X	*NASA
Dai <i>et al.</i> 2018 [62]	ICA:FE – NN – MCC	SoH	-	-	-	NASA + IFP1865140 type LiFePO ₄ battery
Chang <i>et al.</i> 2017 [50]	UKF – EMD – RVM	RUL	~	-	-	*NASA, **CALCE
Chen <i>et al.</i> 2018 [42]	ECM – RLS	SOH	X	-	X	ICR18650-26F LiNMC
Dubarry <i>et al.</i> 2017 [63]	ICA:FE – LUT	SOH	X	-	X	
Li <i>et al.</i> 2018 [32]	(GF):ICA:FE – R	SOH	X	-	-	31.5Ah LiNM
Zhang <i>et al.</i> 2017 [51]	UKF:UPF:MCMC – R	RUL	-	-	-	0.9Ah battery, **CALCE
Sun <i>et al.</i> 2016 [64]	ECM – NN – EKF	SoC	-	X	X	
Temperature approach 2						
Shen <i>et al.</i> 2018 [34]	ECM – EKF – RLS	SoC/SoH/SoF	X	-	X	20Ah LiB
Wang <i>et al.</i> 2017 [65]	(WT):ICA:FE – GP:(GA)	SoH	-	-	-	10Ah pouch LiNMC
Zhang <i>et al.</i> 2018 [46]	ECM:(GA)-PF-RLS	SoC/SoH	X	X	X	38Ah Li(Ni _{1/3} Co _{1/3} Mn _{1/3})O ₂ , NEDC
Zheng <i>et al.</i> 2016 [66]	ECM – UKF	SoC	X	-	X	2.0Ah 18650 LiB
Lin <i>et al.</i> 2017 [67]	ECM – UKF	SoC	X	-	X	25Ah LiNMC, 20Ah LiFePO ₄ (LFP) battery
Temperature approach 3						
Zou <i>et al.</i> 2018 [48]	ECM – MPC	SoP	X	-	X	2.3Ah cylindrical LiFePO ₄ battery
Yang <i>et al.</i> 2016 [61]	R	SoH/RUL	-	-	-	NASA
Mejdoubi <i>et al.</i> 2016 [24]	ECM – AO/EKF	SoC/SoH	X	-	X	20Ah LiFePO ₄ Battery
Dong <i>et al.</i> 2016 [44]	ECM – EKF – PF – R	SoE	X	-	X	9Ah LiFePO ₄ battery
Wang <i>et al.</i> 2017 [45]	ECM – PF – RLS	SoE	X	X	X	100Ah LiFePO ₄ (1665130-type), 72Ah Li(Ni _{1/3} Co _{1/3} Mn _{1/3})O ₂
Wang <i>et al.</i> 2017 [68]	ECM – NN	SoC	-	-	-	20Ah LiFePO ₄
Altaf <i>et al.</i> 2017 [69]	ECM – MPC	SoC	X	X	X	2.3Ah ANR26650M1A
Chemali <i>et al.</i> [70]	LSTM – RNN	SoC	X	-	X	2.9Ah 18650PF
Farag <i>et al.</i> 2017 [59]	EM:(GA)	SoC	X	-	X	26Ah Graphite-NMC LiB
Li <i>et al.</i> 2018 [71]	ECM – CC – LUT	SoE	X	-	X	20Ah LTO
You <i>et al.</i> 2016 [60]	SVM/NN	SoH	X	X	X	3.1Ah 18650 batteries

*NASA battery dataset [72]. ** Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland [73]. PF=particle filter, EKF=Extended Kalman filter, ICA=incremental capacity analysis, GA=genetic algorithms, WT=Wavelet transform, R=Regression, NN=Neural network, PSO=Particle swarm optimization, MPC=Model predictive control, MCC=Markov chain correction, FE=Feature extraction, AO=Adaptive observer, EMD=Empirical mode decomposition, RVM – Relevance vector machine, RLS=Recursive Least squares, LUT=Look-up table, GF=Gaussian filter, MCMC=Markov Chain Monte Carlo, LSTM=Long-short term memory network, RNN=Recurrent neural network, CC=Coloumb counting, EM= Electrochemical model

ideal charge, discharge and EIS operational profiles on Li-ion 18650 sized batteries, cycled until the battery faded 30% from the rated capacity. Figure 3 displays the charge and discharge temperature of battery B0005 from the dataset, which was cycled at 24°C ambient temperature, charging in constant current mode at 1.5A until the battery voltage reached 4.2V and then constant voltage mode until the charge current dropped to 20mA. Discharge carried out at constant load of 2A until the battery voltage fell to 2.7V. The charge and discharge temperatures in Figure 3, demonstrates the obvious relationship between temperature generation and battery aging, and the constant ambient temperature during discharge acts mostly as an initial condition.

In the reviewed literature, the four main methods of addressing temperature dependence are described in section A-D:

A. BATTERY SURFACE TEMPERATURE

It has been proposed that battery surface temperature is correlated with battery capacity [61], as demonstrated in Figure 3d), through the Joule effect and the relationship between internal resistance and capacity [15]. Determining SoH and RUL by surface temperature alone falls in the

category of experimental methods. Yang *et al.* [61] proposed estimation of RUL based on the temperature difference over a full cycle, making it inappropriate for online applications and dynamic cycling. In theory it is scalable to a set of thermally isolated connected cells, however for cells in a pack under real conditions, the flow of heat between cells and the surroundings as well as temperature variation due to thermal management, makes the method impractical.

B. STANDARD ECM, WITH TEMPERATURE CORRECTION

A strategy based on following the general model-based approach of establishing an ECM and incorporating temperature dependence by modelling temperature influence on affected parameters instead of a coupled ECM with a thermal model. El Mejdoubi *et al.* [24] modelled temperature dependence on battery voltage and internal resistance, Dong *et al.* [44] used an open-circuit voltage function of SoE with 6 parameters, where each parameter is a function of temperature. Wang *et al.* [45] used a similar approach by establishing a nonlinear function for open-circuit voltage dependent on SoE and temperature.

This approach can incorporate the effects of dynamic battery temperature but gives an impression that the method

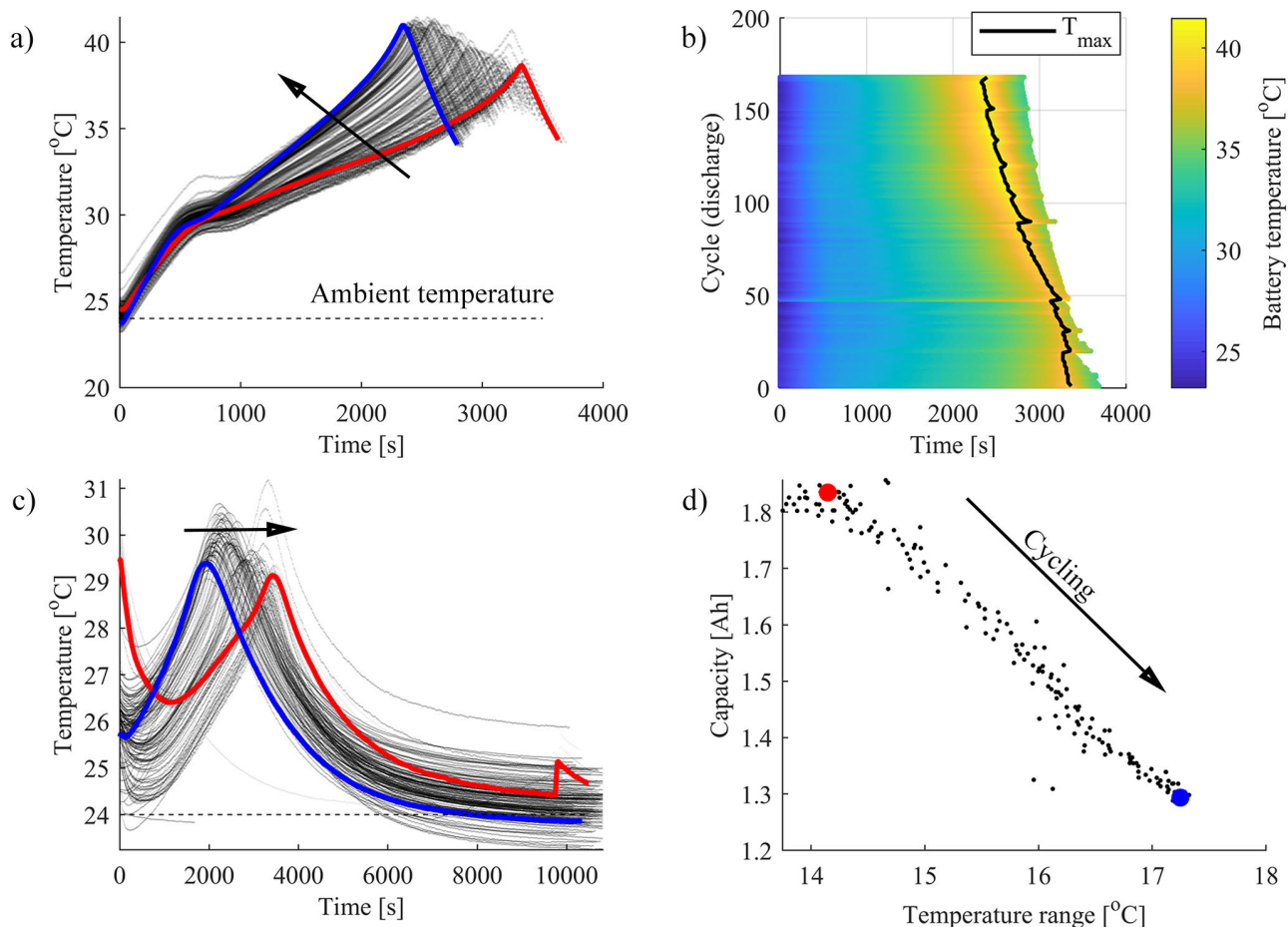


FIGURE 3. NASA battery #5 cycling in constant ambient temperature (24° C): a) discharge temperature, b) maximum discharge temperature over all discharge cycles, c) charge temperature, d) discharge temperature range and capacity during cycling. Nasa battery data #5 Red and blue plotted lines are the initial and end cycles respectively.

is developed without consideration of battery temperature, and then inserting a model temperature dependence in retrospect.

C. ELECTROCHEMICAL AND THERMODYNAMIC COUPLED ECM

A coupled ECM combines the battery model with the energy balance model (3), so that measured temperature can be a part of the state space formulation (1) and (2), see Table 4. Zou *et al.* [48] coupled a 2RC electric model with a thermal cell model for surface, core, average and coolant temperature using a heat generation equation for reversible and irreversible heat, but also used temperature correction of parameters. Wang *et al.* [68] coupled a 1RC model with an energy balance equation including reversible and irreversible heat generation and heat exchange with surroundings. Wang *et al.* in contrast to Zou *et al.* considered the temperature to be uniform throughout the cell. Altaf *et al.* [69] used a simple cell model approach with open-circuit voltage in series with a resistance, and a thermal model for surface temperature dynamics of cells including heat generation within cells

and convective heat transfer between cells. Farag *et al.* [59] specified a coupled model with an electrochemical model, a heat generation model and a thermal model. Farag *et al.* similarly to Wang *et al.* [68] included reversible losses, irreversible losses and heat of mixing. The battery thermal model addressed battery core, housing, bottom and terminal temperature.

The publications in Table 4 are the most comprehensive approaches to solving the problem at hand, and they have different advantages and disadvantages. E.g. Altaf *et al.* is the only solution designed for an actual battery pack and is the only one that takes variation between cells and heat transfer between cells into account. Farag *et al.* provides the most comprehensive model for pouch cells, but estimation of electrochemical model parameters and extending the model to packed cells may be challenging. Wang *et al.* explores the reversible and irreversible heat more thoroughly than Zou *et al.*, but at the same time does not take temperature distribution within cells into account. This may not have a large impact on estimates, but it can have an impact on employing the battery state estimation method in thermal management strategies,

TABLE 4. Coupled ECMs.

Work	Battery Model	Thermal model	Heat generation
Zou <i>et al.</i> [48]	2RC	Non-uniform: core, average, surface, coolant	Irreversible, reversible
Wang <i>et al.</i> [68]	1RC	Uniform, coolant	Irreversible, reversible,
Altaf <i>et al.</i> [69]	1R	Uniform, convection (between cells)	Irreversible,
Farag <i>et al.</i> [59]	EM	Non-uniform: terminal, housing, bottom, core	Irreversible, reversible, mixing, side reactions

EM= (Reduced order) Electrochemical Model, external= coolant or ambient

as described in section II.B.2 regarding potentially harmful effects from surface cooling of cylinder batteries.

D. DATA-DRIVEN

As previously mentioned, the availability of comprehensive failure data is a challenge for the data driven methods. You *et al.* [60] used a neural network (black-box) method with voltage, current and temperature as inputs, and provided a framework for training data collection. Data was collected from different ambient temperatures for dynamic cycling based on dynamometer driving profiles. This approach did not address a way to reduce the amount of necessary data but proposed a way to emulate it, and potentially extend to additional variables. Chemali *et al.* [70] used a Long Short-Term Memory type recurrent neural network, which encoded time dependencies and behavior at different ambient temperatures, and claiming that the need for training data is lower compared to traditional approaches. The trained network was able to generalize to intermediate conditions it was not trained on.

Data-driven methods appear to be a powerful approach for battery state estimation, and with rapid development of machine learning algorithms, hardware and Internet of Things, new opportunities arise which can solve the problems of data scarcity, such as:

- Transfer learning [74], [75]: Adapting trained machine learning algorithms to different but related/similar tasks. For EV applications, the data scarcity problem of batteries is more of a practical problem in terms of collection: The EVs in normal use can generate large amounts of training data, but this is too late in the development cycle, since data must be available prior to product launch. If vast amounts of past *similar* data can be adapted to new systems with less training data, this can provide a way around the data scarcity problem.
- Recurrent networks: Deep Recurrent Neural Networks (DRNN) [76] and LSTM-RNNs [70] have the ability to encode time dependence and nonlinearities well. This could be used in place of or in combination with existing approaches, such as: model-aided learning [77], [78], or DRNN modelling of intricate nonlinear circuits [76], to replace the standard ECM model in the prediction step of adaptive filtering and to reduce the need for online re-optimization of parameters as aging occurs.

E. SUMMARY OF METHODS

Among the published work from 2016 and onward some approaches are only useful for offline diagnostic work; with

fixed conditions, full charge and discharge cycles, omitting the influence of battery temperature. The two approaches that appear to be the most promising for satisfying criteria A-C are:

- *Thermodynamic/electrochemical coupled ECM in combination with adaptive filtering and estimation of unobservable parameters*: Scalability to battery packs (criteria B) is not clear. Altaf *et al.* [69], see Table 4, was most practical in their address of the necessary environment for cells in a battery pack, in that they included heat convection and thermal coupling between cells. They addressed cell to battery pack scaling in a pragmatic way by using the simplest equivalent model (1R) only accounting for irreversible ohmic losses. This demonstrates the major challenge of generalization, that can be approached from two directions:
 - a) Connect n individual (k -parameter) cell models to form a nk -parameter battery pack model
 - b) Approximate the battery pack model as a single k -parameter collective battery model.

There is a trade-off between cell level detail and computation load, but in both cases the computational load is likely going to be the limiting factor. However, cell level detail is desirable in the context of non-uniform aging.

- *Data-driven Neural network-based method*: Given that data-driven solutions can accurately encode battery aging dynamics, can be trained offline and deployed online, the trade-off is not between accuracy and computational load, but between accuracy and available data. but the method requires more comprehensive training data, and needs to be designed with consideration of the data scarcity challenge. From the reviewed literature, You *et al.* [60] proposed a method of data collection by emulation, whereas Chemali *et al.* [70] suggested that LSTM-networks can encode time dependence behavior and requires less data than other data-driven methods.

The thermal management challenge can be addressed by improved monitoring strategies at the cell level and module (pack) level [19]:

- Cell level – modelling of heat generation [56] and temperature distribution within cells with lumped thermal cell models [48], [59] in combination with appropriate cooling strategies, considering that high temperature gradient in a cell can accelerate aging [57], [58].

- Module level – Heat transfer between cells [69] and how it relates to localized accelerated aging and overall aging.

Accurate modelling and rapid estimation of the impact temperature has on battery health under the operating conditions has a potential for improving state estimation in battery management systems, but in the context of thermal management it is more appropriate to consider it as an optimal control problem where the cell and module level models control the cooling strategy, e.g. intense localized cooling to preempt the development of cell clusters aging at an accelerated rate, and prevent the subsequent spread of accelerated aging. However, in practice there is still a major constraint regarding computational complexity from the number of equations (in the case of model-based methods) added by accounting for interactions within and between individual cells without sacrificing dynamic accuracy. Although if accelerated aging occurs among clusters of cells localized in space it may be possible to make lumped models of clusters of cells as a midpoint between modelling individual cells and modeling the battery pack as a whole.

V. CONCLUSION AND PROSPECTS

This review has covered recent literature in the topic of electric vehicle battery state parameter estimation and incorporating the effect of varying temperature as this has a significant impact on the life and performance of batteries, especially in cold climates.

As visualized in Figure 2, battery cells may have a temperature distribution in the pack generated by issues like structural and thermal design of the battery pack as well as process inaccuracies in the battery cell fabrication. Temperatures outside the optimal working range accelerates the aging of cells, and as cells age, the internal resistance increases leading to increased irreversible heat losses. If imbalances develop in a subset of cells, the resulting local accelerated aging may propagate through heat transfer and accelerate the aging of otherwise healthy cells and lead to premature battery failure. Thus, early detection of changes in temperature distribution with an associated temperature dependent battery pack aging model can serve as input to an active thermal management system. However, in any system implementation, change in power consumption and cost of implementation would have to be addressed with respect to the change in performance and battery life to determine the economic viability of the implementation.

ABBREVIATIONS

Ah – Ampere hour
 CPE – Constant Phase Elements
 DVA – Differential voltage analysis
 ECM – Equivalent circuit model
 EIS – Electrochemical Impedance Spectroscopy
 EVs – Electric vehicles
 HPPC – Hybrid Pulse Power Characteristics
 ICA – Incremental capacity analysis
 KF – Kalman filters

LiB – Lithium-ion batteries
 LSTM – Long Short-Term Memory
 PF – Particle filters
 PVs – Petroleum-fueled vehicles
 RNN – Recurrent Neural Networks
 RLS – Recursive least square
 RUL – Remaining Useful Life
 SoAP – State of Available Power
 SoC – State of Charge
 SoH – State of Health
 SoF – State of Function
 T – temperature
 t – time

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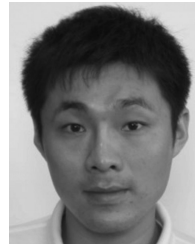
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