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A Review on Battery Performance and Management with Regard to Temperature for Electric Vehicles

Behara Bhuvaneswara Rao[1], Vasupalli Manoj[2], Chebodula Vighnesh[3]

[1,3]*B.Tech Student, Department of Electrical and Electronics Engineering, GMR Institute of Technology,Vizianagaram District, A.P, India*
[2]*Assistant Professor, Department of Electrical and Electronics Engineering, GMR Institute of Technology,Vizianagaram District, A.P, India.*

A B S T R A C T

These days, the world is putting more effort into reducing carbon emissions from conventional automobiles. Electric vehicles have so been introduction to replace conventional vehicles in an effort to cut carbon emissions. However, the motor and battery are the two components that matter most in an electric vehicle. The battery and its management are the key points of this review. Lithium-ion batteries are used in EVs the most frequently, although they have a good temperature range. Outside of this range, however, can result in capacity and power fading, which speeds up ageing. So, we discuss about how temperature affects operational conditions as well as battery performance and health. Various techniques to get around temperature dependence are also included. This article examines how temperature dependence and heat generation are managed in battery state parameter estimation. And various methods to overcome from temperature dependence on battery.

Keywords:Soc,Soh, Kalman Filter,Artificial Neutral Network,Fuzzy Logic,Data Driven Methods,Estimation State of Battery

1.Introduction:

The automotive sector has grown to become one of the most significant global industries, both economically and in terms of research and Development. In order to improve the safety of both passengers and pedestrians, additional technical components are being added to the vehicles. In addition to shared mobility, public transportation, etc., EVs will play a significant role in smart cities. More work is therefore required to improve batteries and the charging process. The primary disadvantage of EVs is their autonomy. To boost driving range while reducing weight, cost, and charging time, scientists are developing better battery technology. LIBS is a prominent electric car battery technology.LIB performance, health, and safety are, however, hindered by thermal management issues. Low temperatures reduce energetic anode material, reducing capacity and power, while high temperatures drain lithium, reducing capacity. Both accelerate battery deterioration. High temperatures can cause distortion, burning, and combustion, which damage battery components and vehicles.This helps with EV battery heat management. Affordable and effective thermal management solutions must take into account inside a battery pack and the temperature's impact on health and performance, particularly when non-uniform speeded up aging process of battery packs as a result of variation between cells is considered. Battery health management (BHM), also called a battery management system (BMS), is crucial in complex systems. BMS controls a battery's utilization, extends its lifespan, saves maintenance expenses, and avoids safety issues. It estimates battery condition using SoC and SOH in power management modules. To accomplish these functions, the BMS must perform battery modelling, state monitoring, and management.This study provides a thorough examination of the variable temperature change in battery packs observed using battery monitoring systems, which can be crucial for cold climatic issues, high thermal security concerns, and overall lifespan and performance.

2.Literature review:

2.1) *Methods for Estimating Battery State:*

Given the nonlinear electrochemical reactions and operational parameters, battery state estimation methods are used to represent the inner battery state, which is essential for operating a battery-powered system properly, sustainably, and safely. State parameters explain three battery characteristics. SoC, SoH, and SoF signify the amount of accumulated charge, the drop in peak performance respect to a new battery, and the battery's power. Three groups. A quick introduction to traditional methodology groups experimental, model-based, and data-driven approaches.

2.1.1) Experimental Methods:

The term "experimental methods" refers to methods that use non-destructive experimental techniques to investigate battery properties.

Coulomb-counting combines the current transmitted to or through the battery over time to calculate the residual charge (SoC), maximum capacity (SoH), or aging of maximum capacity compared to a new battery. Beginning value error and sensor error make this online technique inaccurate. Due of its simplicity, Coulomb-counting is often used with model-based methods. Electrochemical Impedance Spectroscopy (EIS) and Hybrid Pulse Power Characterization (HHPC) are non-destructive electrical response testing methods. HPPC experiments observe voltage changes during higher current charge/discharge cycles separated by rest intervals. The cell voltage response is impacted by power loss, dual layers capacity, and lithium-ion diffusion. EIS uses the impedance spectrum to describe variable battery functions and estimate carrier's movement and reaction rates. EIS investigates current and voltage at variable frequency.

To determine changes in electrochemical parameters, incremental capacity analysis (ICA) and differential voltage analysis (DVA) examine the changes in charge (Q) and battery voltage (V) in a cell at equilibrium during charging/discharging [30]. By identifying feature points from IC and DV curves and analysing change-over ageing, numerous degradation patterns can be determined. ICA/DVA analysis in live application must differentiate arbitrary noise, assume equilibrium conditions, and create IC-DV curves when operating conditions affect discharge.

The experimental approaches by themselves are best for offline mode SoH determination due to full cycles, consistent temperatures, and a disconnected battery. Online SoH detection with partially ICA charging data or online EIS for fueling cell EVs have been attempted. Experiments are often combined with prototype methods like HPPC to determine model parameters**.**

2.1.2)Methods Based OnModels:

An approximate equivalent model isused to depict battery dynamics in the model-based approach, and available sensor data is adaptively filtered to estimate unobservable state parameters.

2.1.2.1) Equivalent Circuit Models:

ECMs for LiB cells are used to characterise battery Voltage-Current characteristics. ECMs can be designed for accuracy, computational burden, parameter estimates, and reliability. Experimentation and optimization can determine model parameters. No obvious way exists to determine the best ECM given a battery's technology, sort, and application. If multiple studies on computational load use different optimization methodologies, their conclusions and suggestions may not be equivalent. When balancing accuracy, performance, and reliability, simple models are usually preferred. Table-1 displays many approaches.

TABLE-1: ECM RECOMMENDATIONS

S.NO	WORK	optimisation	Battery Type	Recommended ECM
1.	Heetal.2011	Initial Regression+(unspecified) Genetic Algorithm	$LIMN_2O_4$	2RC
2.	Huet.al	Multi particle-swarm optimisation	LINMC,$LIFePO_4$	1RC
3.	Westeroffet al	Initial Regression+trust-region	$LIN_{1/3}Mn_{1/3}Co_{1/3}O_2$	For EV:>=3RC or 1RCPE
4.	Laietal	Non-linear programming physics-evolution	LINMC	>=2RC-H is not suited for online

2.1.2.2)Adaptive Systems:

Adaptive filters aren't merely signal-processing tools. It's a self-designing system with an adaptivealgorithmfor updating settings and autonomous system changes. Cars use this filter. Hybrid and electric vehicle (HEV) rate profiles are dynamic, and current as a function of time is stochastic. KF, ANN, FL, and their variations are the most utilised adaptive filters.

2.1.2.2.1) Kalman Filter (KF):

Kalman Filter (KF) helps reduce measurement noise and approximate a system's condition that cannot be directly observed (i.e SOC or SOH). KF combines a measuring set and a data base. The approach consists of many equations that calculate a value. KF adjusts the prediction by comparing it to the actual measurement. When compared to the actual measured value, this value is corrected by the Kalman filter estimation. KF is modelled as a state space with a processing equation and a measuring equation. Here's the discrete-time linear model. Processing equation is a linear function that calculates xk from xk1-1. Measuring formulas get the estimated value closer to the genuine value.

$X_K = A_{XK}-1 + B_{UK}-1 + w_{K-1}$--(1)

$Z_K = C_{XK} + D_{UK} + V_K$ --(2)

Kalman Filter has five equations, two for predicting and three for correction. To explain, v^ means estimated V value and V- means a priori V value. Prediction equations are:

$x\hat{}- k = A_{X^K-1} + B_{UK-1} + w_{K-1}$-- -(3)

$P - k = A_{PK-1}AT + Q$---(4)

Correction equations are given by:

$K_K= P - k\ HT\ (H\ P - k\ HT + R)\ -1$;-(5)

$X\text{^}k = \hat{}X_{-K} + K_K\ (Z_K- H_{X^K-1})$;-(6)

$P_K = (I - K_K\ H)\ P_{-K}$;-(7)

2.1.2.2.2)Artificial Neural Network (ANN):

ANNs are data-based models whose paradigm is taken from the brain. This paradigm shows how ANN can model complex nonlinear networks like State-of-Charge or State-of-Health. Neurons in an ANN are linked to connect inputs and outputs.

n = p1 w1,1 + p2 w1,2 + b; a = f (n)-(8)

The activation function could be sigmoid, nonlinear, or another function. There are three layers for ANN. They are Input, hidden, and output layers.

Like the human brain, ANN must learn. The neural network is training. This phase sets the best neuron weight. Training uses a number of algorithms. ANN learning used back propagation. It examines Lithium-ion battery discharge trends. ANN's paradigm can provide battery information (SOC and SOH). This adaptive system's training phase requires a lot of data to be useful.An evaluation phase using a final sample is utilised to verify the ANN accuracy.State-of-Charge and State-of-Health are quite difficult to define with a straightforward ANN. This is a result of both the system's complexity and the training process. An ANN can only be used for one type of application at a time. Input conditions change fast in hybrid electric vehicles, making testing difficult. Adaptive neural networks can evaluate prediction results.

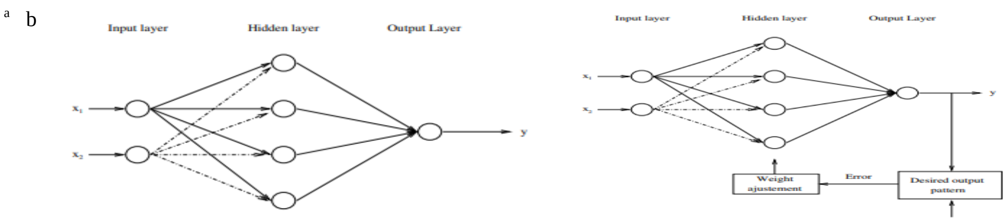

fig-1:(a) AThree Layer of Artificial Neutral Network;(b) Three Layer of Artificial Neutral Network

2.1.2.2.3*)Fuzzy Logic(FL):*

An adaptive system called fuzzy logic (FL) can determine a genuine value based on actual input and by applying arbitrary rules. In [36], fuzzy logic is used to estimate a person's state of health and charge. The bases of fuzzy logic are discussed here with a summary that applies to SOH. Crisp or fuzzy sets can be used to categorise data. Data are concretely categorised by crisp sets. State-of-Health evaluation results range from 0% to 100%. The State-of-Health for fuzzy data sets is low. Low's eligibility function defines it as a subset of all values. A set element's degree of membership specifies how much it belongs to fuzzy subset low. Figure shows three State-of-Health subsets characterised by weak, correct, and new. Fuzzification of real-valued data determines fit values. Figure below demonstrates a fuzzy system with real-valued input and output. There are four conceptual parts to the fuzzy system:

1.A defuzzification block that turns fuzzy output to crisp,

2.An inference-making method

3.A data that defines output and input variable membership functions, and

4.A rule base that characterises their relationship.

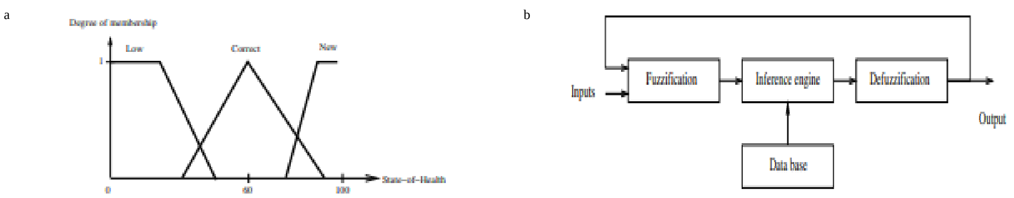

FIG-2:(a) Membership Function for State-Of-Health; (b) Fuzzy Logic System

2.1.3) Data-Driven Methods:

Data-driven strategies can give reliable and rapid results with enough training data. When innovation on battery technologies were released, it can be hard to gather failure data for commercial training. Battery dynamics make straight recycling of trained models difficult. Collecting adequate training data is critical, but it may be problematic if battery pack structure, layout, cell chemistry, etc. modifications render old data unrepresentative and require obtaining new data. Over- or underfitting can cause problems. Is the data set representative of all relevant scenarios, or are some missing? Model-based techniques and experimental procedures for SoH, as stated by You et al., often rely on limited hypothesis such as complete cycling with fixed current, which is not reflective of partial and variable cycling in real-world operation.

3.)Methodology:

3.1)Temperature-Dependent Methods Criteria:

The three categories of temperature are addressed by the examined battery monitoring techniques:

1) Avoid temperature fluctuations and battery heat.

2) Update model parameters often if they're temperature-dependent. 1) Validate the model for a larger range of temperature or update model parameters when battery temperature drifts.

3.) Use existing sensor data (e.g temperature, voltage, current). Present cycle temperature, historic charge/discharge cycle statistics, or real-time temperature.

There are three types of methods to overcome the battery management and its' behaviour. They are:

3.1.1)Online Prediction

3.1.2)Battery Pack

3.1.3)Dynamic Profiles

3.1.1) Online Prediction:

The approach must be able to forecast SoC/SoH or other state parameters while driving and integrate with the battery management systems. Non-destructive, fast, accurate, and controllable computational intensity are required. Stationary charging allows concessions. On a static shut-down vehicle, more detailed offline diagnostic procedures may be performed, such as full/partial battery charge cycle measurements.

3.1.2)Battery Pack:

From a solitary cell to a battery pack challenging needs scalability to an application-dependent number of cells with layout cell interaction. One ECM can be linked to every cell, but based on the number of cells, the model may require customization of many different parameters, additional measurement and testing dataset, and be computationally expensive.On the other hand, if the collection of linked cells is taken into the number of parameters is one equivalent model with one parameter.It will be manageablebut unable to record inter-cell variance. The behaviour of newly formed cells with the same chemical is consistent. Subsets of cells cycled at severe temperatures enhance non-uniform ageing. Fabrication procedures, battery pack layout, and heat management might cause this. Aged batteries generate heat (see Figure), which can accelerate cell degradation. Temperature affects decay. When considering thermal management and equalize solutions for cells with various SoH and SoC, it's necessary to consider how heat generation inside the cells, transfer heat among cells, and heat transmission with environment relate to SoH.

***3.1**.3) Dynamic Profiles:*

Even with a fixed ambient temperature, battery cell temperature will change due to energy saving. since electrochemical reactions are temperature-dependent. Cell temperatures can predict SoC, SoH, and SoP. In real-world applications, conditions are rarely optimal and often unknown in advance, such as fluctuating ambient temperature and part battery pack discharge based on travel distance, traffic, and road conditions.

TABLE-2: Battery State Estimation

S.NO	WORK	METHOD	PARAMETER	A	B	C	BATTERY
TEMPERATURE APPROACH 1							
1.	Duong etal.2018	HKF-PF-R	RUL	_	_	_	NASA
2.	Yang etal.2018	ECM-R	SOH	X	_	_	2.5Ah $LiFePO_4$batteries
3.	Yuetal.2017	PF-R	SOH	X	_	X	NASA
4.	Dai etal.2018	ICA:FE-NN-MCC	SOH	_	_	_	NASA+IFP1865140 type $LiFePO_4$ battery
5.	Chang etal.2017	UKF-EMD-RVM	RUL	~	_	_	NASA,CALCE
6.	Chen etal.2018	ECM-RLS	SOH	X	_	X	ICR18650-26FLiNMC

7.	Dubarry etal.2017	ICA:FE-LUT	SOH	X	_	X	
8.	Lietal.2018	(GF):ICA:FE-R	SOH	X	_	_	31.5AhLiNM
9.	Zhang etal.2017	UKF:UPF:MCMC-R	RUL	_	_	_	0.9Ah battery,CALCE
TEMPERATURE APPROACH 2							
10.	Shenetal.2018	ECM-EKF-RLS	SOC/SOH/SOF	X	-	X	20Ah LiB
11.	Wangetal.2017	ICA:FE-GP:GA	SOH	_	_	_	10Ah pouch LiNMC
12.	Zhangetal.2018	ECM:GA-PF-RLS	SOC/SOH	X	X	X	NEDC,38Ah $Li(Ni_{1/3}Co_{1/3}Mn_{1/3})O_2$
13.	Zhangetal.2016	ECM-UKF	SOC	X	_	X	2Ah 18650 LiB
14.	Linetal.2017	ECM-UKF	SOC	X	_	X	25Ah LiNMC,20Ah(LFP)battery
TEMPERATURE APPROACH 3							
15.	Zouetal.2018	ECM-MPC	SOP	X	_	X	2.3Ah cylindrical LFP battery
16.	Yangetal.2016	R	SOH/RUL	_	_	_	NASA
17.	Mejdoubietal.2016	ECM-AO/EKF	SOC/SOH	X	_	X	20Ah LFP battery
18.	Dongetal.2016	ECM-EKF-PF-R	SOE	X	_	X	9Ah LFP battery
19.	Wangetal.2017	ECM-PF-RLS	SOE	X	X	X	100Ah LFP Battery(1665130)
20.	Wangetaal.2017	ECM-NN	SOC	_	_	_	20Ah LFP
21.	Altafetal.2017	ECM-MPC	SOC	X	X	X	2.3Ah ANR26650M1A
22.	Chemalietal.	LSTM-RNN	SOC	X	_	X	2.9Ah18650PF
23.	Faragetal.2017	EM:(GA)	SOC	X	_	X	26Ah graphite-NMC LiB
24.	Lietal.2018	ECM-CC-LUT	SOE	X	_	X	20Ah LTO
25.	Youetal.2016	SVM/NN	SOC	X	X	X	3.1Ah 18650 batteries

4.Results and Discussions:

Approaches 1 and 2 presume ambient temperature is a reference for battery temperature and the battery can function under fixed conditions. The NASA Ames Prognostics Center of Excellence battery dataset is used in such instances (see Table). NASA's data collection includes charging, discharging, and EIS operational profiles for 18650 Li-ion batteries cycled to 30% capacity. Figure 3 illustrates the charged and discharge temperature of battery B0005, which has been cycled at 24oC ambient temperature, charged at 1.5A till the battery voltage level achieved 4.2V and then at fixed voltage until the charge current fell to 20mA. At 2A constant load, discharged until 2.7V. Figure 3's charge and discharge temperatures show the link between temperature output and battery ageing. Starting condition is steady ambient temperature during discharge.

Sections 4.1-4.4 cover the four basic strategies for managing temperature dependence.

4.1) Battery surface temperature:

Figure shows how the Joule effect and internal resistance link battery surface temperature to capacity [61]. Surfaces temperature determines SoH and RUL. Yang et al. [61] determined RUL based on full-cycle temperature differential, which is insufficient for online and dynamic cycling. The system can be scaled to a group of thermally isolated, linked cells, but for cells in a packing, heat exchange among cells and the environment and temperature change make it impractical.

4.2)Standard ECM, with temperature correction:

A strategy focused on building an ECM and modelling temperature dependence. Dong et al employed SoE open-circuit voltage with 6 temperature-dependent parameters. Wang et al. [45] modelled SoE and temperature to develop a nonlinear open-circuit voltage function. This method can accommodate variable battery temperature, but temperature dependence is applied retroactively.

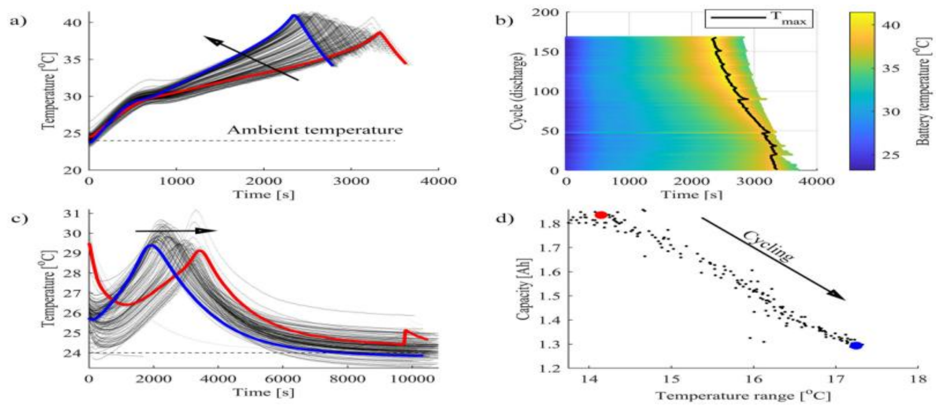

FIG-3:(a) Discharge Temperature;(b) Maximum Discharge Temperature Over All Discharge Cycles;(c) Charge Temperature, (d)Discharge Temperature Range and Capacity During Cycling.

4.3.)Electrochemical and thermodynamic coupled ECM:A connected ECM combines the battery model and energetic balance model (3) to include measured temperature in (1) and (2). (2). Zou et al. [48] coupled a 2RC electric model with a thermal cell model for surface, core, average, and coolant temperature. Wang et al. [68] employed a 1RC model with a heat balance equation. Wang et al. directly compared Zou's cell temperature. Altaf et al. [69] used a simple cell model with open-circuit voltage and resistance, and a thermo modeling for cell surface temperature variations, involving heat generation within cells and convective heat movement between cells. Farag et al. incorporated electrochemical, heat-generating, and thermal models. Reversible, irreversible, and mingling losses were added by Farag et al. Core, housing, bottom, and endingtemperatures were modelled.The table-3 illustrates the problem's most thorough remedies, with pros and cons. Altaf et al. is the only solution that addresses cell variance and heat transmission. Farag et al. give the most thorough model for pouch cells, although expanding it to packed cells may be tricky. Wang et al. look more closely at reversible and irreversible heat than Zou et al. This may not impact estimations considerably, but it can adversely effect thermal management tactics (part II). B.2 surface battery cooling.

TABLE-3: COUPLED ECM'S

S.NO	WORK	BATTERYMODEL	THERMALMODEL	HEATGENERATION
1.	Zouetal.	2RC	Core avg surface	irreversible,reversible
2.	Wangetal	1RC	Uniform,coolant	irreversible,reversible
3.	Altafetal	1R	Uniform	irreversible
4.	Faragetal	EM	Terminal,core	irreversible,reversible,mixing

4.4.)Data-driven:

Data-driven techniques lack failure data.A neutral network received voltage, current, and temperature. Cycling profiles employed different ambient temperatures. This strategy proposed replicating it and providing more variables, not reducing data. Chemali et al.Employed a recurrent neural networks to generate time dependencies and performance at different temperatures. In intermediate situations, the trained network generalised.

With the rapid growth of machine learning algorithms, technology, and the Internet of Things, fresh opportunities to tackle data scarcity challenges, such as:

• Transfer learning: Applying machine learning to similar activities.Electric vehicle battery data is scarce.Normal EV use can provide training data, but it is too later in the development process; data must be accessible before product introduction. Data scarcity can be alleviated by adapting similar prior information to new system with less training data.

4.4.1) Recurrent Networks:

DRNN and LSTM-RNNs convey time dependency and nonlinearity well. This could be used instead of or in combination with model-aided learning or DRNN modelling of sophisticated nonlinear circuits to replace the traditional ECM model in the prediction phase of adaptive filtering and eliminate the necessity for online re-optimization of parameter as ageing occurs.Some offline methods require stable circumstances, full charge and discharge cycles, and no battery temperature. The best A-C approaches are:

• ECM with adaptive filtering and unobservable parameter estimation: B) Battery packs aren't scalable.

Altaf et al. [69], see Table, addressed battery cell convection and thermal coupling most practically. Using solely irreversible ohmic losses, they scaled cells to battery packs (1R). This demonstrates the issue of generalisation, which can be overcome in two ways.

a.) Connect n_K-parameter cell models to construct a battery pack model.

b) Model the battery pack with k parameters.

Both examples are likely limited by computational load. Non-uniform ageing is cell-level.

• Neutral Network-based method: Data-driven systems can effectively capture battery ageing processes, be taught offline, and be applied online. The trade-off is accuracy versus available data. Data scarcity must be considered when training the technique. Chemali et al. indicated LSTM-networks can encode time-dependent functionality and required less data than other data-driven techniques.

• Cell level – modelling of heat production [56] and temperature distribution inside cells with gets lumped thermal cell models 48], [59] in collaboration with proper cooling techniques, since strong temperature gradient in a cell can speed ageing [57], [58].

4.4.2) Model level:

Heat transfer and accelerated ageingAccurate modelling and timely assessment of temperature's impact on battery health could improve battery management system status estimation. In the domain of thermal control, it is more suitable to consider it an optimum control issue where cell and modules level models regulate the cooling strategy,e.gintensive localised cooling to prevent accelerated cell cluster ageing. In practise, computing complexity is restricted by the number of equations needed to simulate cell interaction without compromising dynamic accuracy. If accelerated ageing happens in clusters of localised cells, lumped models of clusters may be a halfway among representing particular cells and representing pack as unit.

5.) Conclusions:

This review covers contemporary literature on electric vehicle battery state parameter estimates and temperature, which affects battery Life and performance in cold areas.Due to structural and thermal design flaws or production errors, battery cells may have a temperature spread, as seen in Figure. Outside the ideal range, cells age and internal resistance increases, causing permanent heat loss. If imbalances occur in a fraction of cells, localized accelerated ageing may spread through heat transfer, cause early battery failure. Observing temperature distribution changes early can feed an active and involved thermal management system. Any implementation stage must analyse power consumption, cost, performance, and longer battery life to be economically viable.

REFERENCES

[1]. Sanguesa, J.A.; Torres sanz, v., Garrido, p., Martinez, F.J.; Marquez-Barja,J.M . A Review on Electric vehicles: Technologies and Challenges. Smart cities 2021,4,372-404

[2]. A review of stochastic battery models and health management Laifa Taob,c,d,1, Jian Maa,b,1, Yujie Chengb,c,1, Azadeh Noktehdand,e , Jin Chongf , Chen Lua,b,,2

[3]. A comprehensive review of on-board State-of-Available-Power prediction techniques for lithium-ion batteries in electric vehicles Alexander Farmanna,c* , Dirk Uwe Sauera,b,

[4]. Q. Wang, B. Jiang, B. Li, and Y. Yan, ‘‘A critical review of thermal management models and solutions of lithium-ion batteries for the development of pure electric vehicles,’’ Renewable. Sustain. Energy Rev., vol. 64, pp. 106–128, Oct. 2016

[5]. F. Sun, R. Xiong, and H. He, ‘‘A systematic state-of-charge estimation framework for multi-cell battery pack in electric vehicles using bias correction technique,’’ Appl. Energy, vol. 162, pp. 1399–1409, Jan. 2016

[6]. N. Watrin, B. Blunier, and A. Miraoui, ‘‘Review of adaptive systems for lithium batteries state-of-charge and state-of-health estimation,’’ in Proc. IEEE Transp. Electrific. Conf. Expo (ITEC), Jun. 2012, pp. 1–6

[7]. M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, and P. Van den Bossche, ‘‘Critical review of state of health estimation methods of Li-ion batteries for real applications,’’ Renew. Sustain. Energy Rev., vol. 56, pp. 572–587, Apr. 2016

[8]. S. M. Rezvanizaniani, Z. Liu, Y. Chen, and J. Lee, ‘‘Review and recent advances in battery health monitoring and prognostics technologies for electric vehicle (EV) safety and mobility,’’ J. Power Sources, vol. 256, pp. 110–124, Jun. 2014.

[9]. R. Xiong, F. Sun, Z. Chen, and H. He, ‘‘A data-driven multi-scale extended Kalman filtering based parameter and state estimation approach of lithium-ion olymer battery in electric vehicles,’’ Appl. Energy, vol. 113, pp. 463–476, Jan. 2014.

[10]. Battery Management Systems in Electric and Hybrid Vehicles Yinjiao Xing 1, Eden W. M. Ma 1, Kwok L. Tsui 1,2 and Michael Pecht

[11]. Manoj, V., Sravani, V., Swathi, A. 2020. A multi criteria decision making approach for the selection of optimum location for wind power project in India. EAI Endorsed Transactions on Energy Web, 8(32), e4

[12]. Dinesh, L., Sesham, H., & Manoj, V. (2012, December). Simulation of D-Statcom with hysteresis current controller for harmonic reduction. In 2012 International Conference on Emerging Trends in Electrical Engineering and Energy Management (ICETEEEM) (pp. 104-108). IEEE

[13]. Manoj, V. (2016). Sensorless Control of Induction Motor Based on Model Reference Adaptive System (MRAS). International Journal For Research In Electronics & Electrical Engineering, 2(5), 01-06.

[14]. V. B. Venkateswaran and V. Manoj, "State estimation of power system containing FACTS Controller and PMU," 2015 IEEE 9th International Conference on Intelligent Systems and Control (ISCO), 2015, pp. 1-6, doi: 10.1109/ISCO.2015.7282281

[15]. Manohar, K., Durga, B., Manoj, V., & Chaitanya, D. K. (2011). Design Of Fuzzy Logic Controller In DC Link To Reduce Switching Losses In VSC Using MATLAB-SIMULINK. Journal Of Research in Recent Trends.

[16]. Manoj, V., Manohar, K., & Prasad, B. D. (2012). Reduction of switching losses in VSC using DC link fuzzy logic controller Innovative Systems Design and Engineering ISSN, 2222-1727

[17]. Dinesh, L., Harish, S., & Manoj, V. (2015). Simulation of UPQC-IG with adaptive neuro fuzzy controller (ANFIS) for power quality improvement. Int J Electr Eng, 10, 249-268.