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DESIGN AND IMPLEMENTATION OF BATTERY MANAGEMENT SYSTEM FOR ELECTRIC VEHICLES

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Abstract : Accurate estimation of Li-Ion batteries life cycle is important to the battery management system (BMS). Compared to direct measurement methods and model-based methods, data-driven methods are drawing much attention for online SOH estimation due to their simple structure, flexibility for online application, and independence on battery model. Data-driven methods first extract a strong health indicator (HI) to measure the SOH and then build a machine learning model to map the relationship between them. Based on data analytics on the battery ageing data, this project proposes to use a partial charge and discharge current sequence. Then it is then fed into KNN algorithm, which has fast learning speed and good generalization property. By selecting charging and discharging capacity, the impact on the estimation accuracy is comprehensively evaluated. The proposed method is tested with an open dataset and the results verify the effectiveness of the proposed method. This project provides a review of the main battery SOH estimation methods, enlightening their main advantages and pointing out their limitations in terms of real time automotive compatibility and especially hybrid electric applications.

***Index Terms* – Battery Management, Lithium Ion.**

I. INTRODUCTION

A lithium-ion battery or Li-ion battery (abbreviated as LIB) can store electric energy as chemical energy. Both non-rechargeable and rechargeable LIBs are commercially available. The non-rechargeable LIBs (also called primary cells) have long shelf-life and low self-discharge rates, and are typically fabricated as small button cells for e.g. portable consumer electronics, arm watches and hearing aids. Rechargeable LIBs (also named secondary cells) are applied in all kinds of consumer electronics, and is currently entering new markets such as electric vehicles and large-scale electricity storage. The rechargeable LIBs can be used to supply system level services such as primary frequency regulation, voltage regulation and load shifting, as well as for local electricity storage at individual households. Below we only focus on the rechargeable LIBs.

A LIB contains two porous electrodes separated by a porous membrane. A liquid electrolyte fills the pores in the electrodes and membrane. Lithium salt (e.g. LiPF6) is dissolved in the electrolyte to form Li+ and PF6- ions. The ions can move from one electrode to the other via the pores in the electrolyte and membrane. Both the positive and negative electrode materials can react with the Li+ ions. The negative electrode in a LIB is typically made of carbon and the positive of a Lithium metal oxide. Electrons cannot migrate through the electrolyte and the membrane physically separates the two electrodes to avoid electrons crossing from the negative to the positive electrode and thereby internally short circuiting the battery. The individual components in the LIB are presented in Figure 1.

When the two electrodes are connected via an external circuit the battery start to discharge. During the discharge process electrons flow via the external circuit from the negative electrode to the positive. At the same time Li+ ions leaves the negative electrode and flows through the electrolyte towards the positive electrode where they react with the positive electrode. The process runs spontaneously since the two electrodes are made of different materials. In popular terms the positive electrode “likes” the electrons and the Li+ ions better than the negative electrode.

The energy released by having one Li+ ion, and one electron, leaving the negative electrode and entering the positive electrode is measured as the battery voltage times the charge of the electron. In other words the battery voltage - also known as the electromotive force: EMF - measures the energy per electron released during the discharge process. EMF is typically a around 3-4

Volts and depends on the LIB cell chemistry, the temperature and the state of charge (SOC – see below). When e.g. a light bulb is inserted in the external circuit the voltage primarily drops across the light bulb and therefore the energy released in the LIB is dissipated in the light bulb. If the light bulb is substituted with a voltage source (e.g. a power supply) the process in the battery can be reversed and thereby electric energy can be stored in the battery.

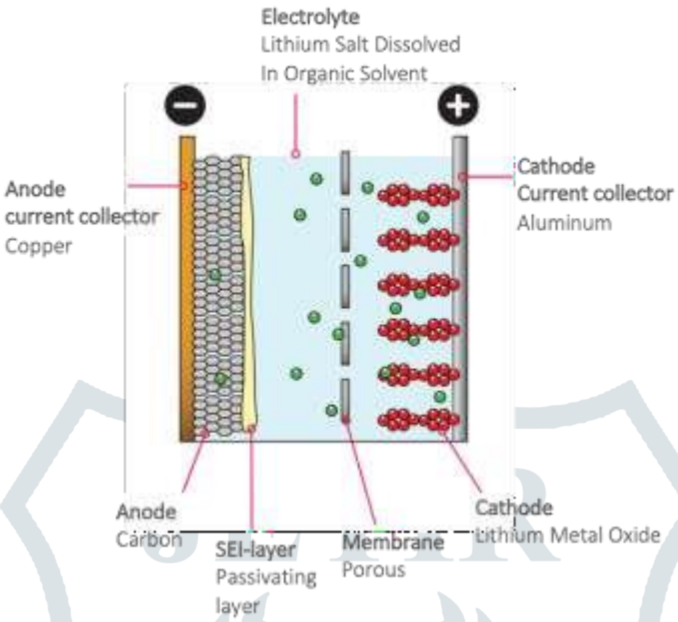

Figure 1. Schematic diagram of a typical LIB system displaying the individual components in the battery.

The discharge and charge process is outlined in Figure 2. The battery is fully discharged when nearly all the Lithium have left the negative electrode and reacted with the positive electrode. If the battery is discharged beyond this point the electrode chemistries become unstable and state degrading. When the LIB is fully discharged the EMF is low compared to when it is fully charged. Each LIB chemistry has a safe voltage range for the EMF and the endpoints of the range typically define 0% and 100% state of charge (SOC). The discharge capacity is measured in units of Ampere times hours, Ah, and depends on the type and amount of material in the electrodes.

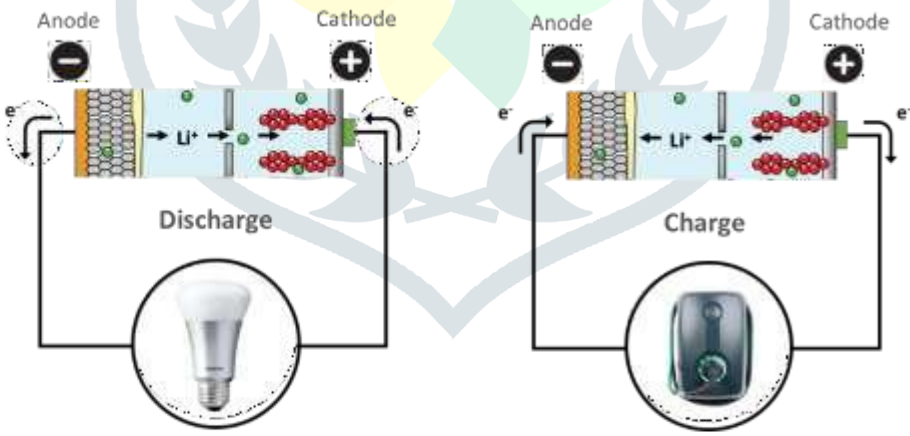

Figure 2. Schematic diagram of a LIB system in charge and discharge mode. During discharge the green Li+ ions moves from the negative electrode (left side) to the positive electrode. The process is reversed during charge mode (right side).

The first lithium batteries were developed in the early 1970"ies and Sony released the first commercial lithium-ion battery in 1991. During the „90s and early 2000s the LIBs gradually matured via the pull from the cell-phone market. The Tesla Roadster was released to customers in 2008 and was the first highway legal serial production all-electric car to use lithium-ion battery cells. Further, around 2010 the LIBs expanded into the energy storage sector.

1.1 Lithium-ion chemistries

Short name	Name	Anode	Cathode	Energy density Wh/kg	Cycles	Calendar life	Major manufactures
NMC	Lithium Nickel Manganese Cobalt Oxide	Graphite	$Li\ Ni_{0.6}Co_{0.2}Mn_{0.2}O_2$	120-300	3000-10000	10-20 years	Samsung SDI, LG Chem SK Innovation, Leclanche Kokam

LFP	Lithium Iron Phosphate	Graphite	$LiFePO_4$	50-130	6000-8000	10-20 years	BYD/Fenecon Fronius/Sony
LTO	Lithium Titanate	$LiTO_2$	$LiFePO_4$ or Li $Ni_{0.6}Co_{0.2}Mn_{0.2}O_2$	70-80	15000-20000	25 years	Leclanche Kokam Altairnano

Table 1 shows a comparison of the three most widely used LIB chemistries for grid-connected LIB systems and the major manufactures. Other LIB chemistries such as LCO, LMO and NCA are not used for grid electricity storage and are therefore not included in the table. The numbers in the table are taken from cell manufactures, product or system suppliers. NMC is the most widely used of the three chemistries due to the increased production volume and lower prices lead by the automotive sector. The NMC battery has a high energy density but uses cobalt. The environmental challenges in using cobalt are described in the section: "Environment".

The LFP battery do not use cobalt in the cathode, but are not as widely used as NMC, and are therefore generally higher priced, primarily due to the lower production volumes. Both NMC and LFP batteries have graphite anodes. The main cause for degradation of NMC and LFP LIBs is graphite exfoliation and electrolyte degradation which in particular occur during deep cycling. LTO LIBs are the most expensive cell chemistry of the three. In LTOs the graphite anode is replaced with a Lithium Titanate anode. The cathode of a LTO battery can be NMC, LFP or other battery cathode chemistries. The LTO battery is characterized by long calendar lifetime and high number of cycles.

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Table 1. A comparison of four widely used LIB chemistries.

Residential energy storage system. All other systems are multi-MWh size.

1.2 Lithium-ion battery packaging

The most common packaging styles for LIB cells are presented in Figure 3. Examples are provided in Figure 4. Figure 3(a) show a schematic drawing of a cylindrical LIB cell. Cylindrical cells find widespread applications ranging from laptops and power tools to Tesla‟s battery packs. Figure 4(a) shows Tesla‟s 21700 cylindrical LIB cell which is 21 mm in diameter and 70 mm in length. The cell is produced in Tesla‟s Gig factory 1 for Tesla Model. Figure 3(b) outline a coin LIB cell. Coin cells are usually used as primary cells in portable consumer electronics, watches and hearing aids. Since they are not used for secondary cells (rechargeable) in grid-connected LIB Battery Energy Storage Systems they are not described further in this text. Figure 3(c) displays a schematic drawing of a prismatic LIB cell. Prismatic LIB cells are often used in industrial applications and grid-connected LIB Battery Energy Storage Systems. The Samsung SDI prismatic LIB cell is shown in Figure 4(b). This cell type is used in the BMW i3. Figure 3(d) shows a schematic drawing of a pouch LIB cell. Figure 4(c) shows an LG Chem pouch NMC LIB cell used in LG Chem‟s grid-connected LIB Battery Energy Storage Systems. Pouch LIB cells are also used in electric vehicles such as the Nissan Leaf.

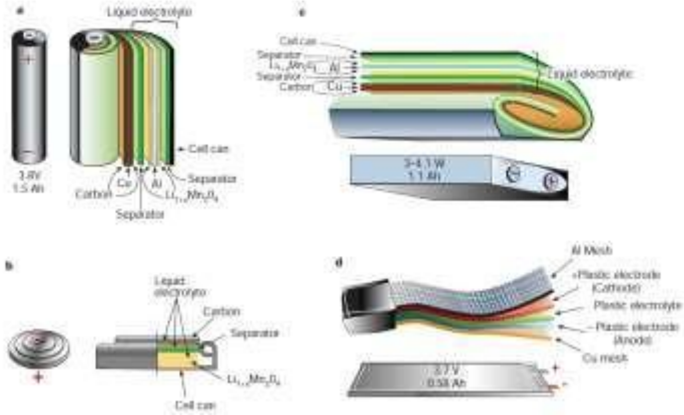

Figure 3. Schematic drawing showing the shape, packaging and components of various Li-ion battery configurations [12].
(a) Cylindrical; (b) coin; (c) prismatic; and (d) pouch.

Figure 4. Examples of LIB cells. (a) Tesla 21700 cylindrical NMC LIB cell. (b) Samsung SDI prismatic LIB cells. (c) LG Chem pouch NMC LIB cell.

1.3 Problem Statement

The main necessity to predict the life of the li-ion battery is to prevent from other health batteries to get destroyed because huge capacity of the li-ion batteries are formed by connecting single cells into series and parallel so if one cell gets damages it slowly starts destroying the other ones. And the other thing is The market for second use EV batteries is poised to grow rapidly as new EV fleet generations go into service. These batteries have a significant amount of residual capacity after their vehicle life has been completed and can be repurposed for various other use case applications, e.g. energy storage solutions behind the facility meter. This poster will present a data-driven analysis of state-of-health and performance found in a population of used EV battery backs.

1.4 Scope

The scope of this methodology encompasses the development of a comprehensive framework for estimating the State of Health (SOH) of Li-Ion batteries using the K-Nearest Neighbors (KNN) algorithm. It includes data collection, feature extraction, health indicator definition, model training, hyper parameter tuning, and impact evaluation. The methodology aims to address a wide range of operating conditions, charging/discharging cycles, and battery health states, ensuring robustness and reliability in SOH estimation. Additionally, it facilitates the analysis of the algorithm's performance under varying conditions and provides insights into its generalization ability.

1.5 Objective

The objective of the outlined methodology is to develop a robust framework for estimating the State of Health (SOH) of Li-Ion batteries using a K-Nearest Neighbors (KNN) algorithm. By collecting a diverse dataset encompassing battery aging data, extracting relevant features, defining a strong health indicator, and implementing and fine-tuning the KNN algorithm, the aim is to accurately capture degradation patterns and variations in battery performance. Additionally, the methodology seeks to assess the impact of different operating conditions on estimation accuracy and validate the effectiveness of the proposed method through rigorous testing and validation procedures.

1.6 Basic Concepts

Data Collection: A comprehensive dataset containing Li-Ion battery aging data, inclusive of partial charge and discharge current sequences, is acquired. Emphasis is placed on diversity, ensuring a range of operating conditions, charging/discharging cycles, and battery health states are represented.

Feature Extraction: The acquired data undergoes preprocessing to extract pertinent features that characterize the partial charge and discharge current sequences. Key parameters, notably charging and discharging capacity, are identified for integration as features for subsequent algorithmic analysis, particularly within the K-Nearest Neighbors (KNN) framework.

Health Indicator Definition: A robust health indicator (HI) is defined based on the selected features, aiming to accurately depict the State of Health (SOH) of the Li-Ion battery. This HI is engineered to encapsulate degradation patterns and performance variations observed over time, providing a holistic assessment of the battery's condition.

Data Splitting: The dataset is partitioned into training and testing sets to facilitate method evaluation. A significant portion of the dataset is allocated for training the KNN algorithm, with the remaining portion reserved for testing the model's performance, ensuring a robust assessment of its efficacy.

K-Nearest Neighbors (KNN) Algorithm: The KNN algorithm is implemented using the training dataset to discern the relationship between the defined health indicator and the partial charge and discharge current sequences. Exploration of different 'k' values (number of neighbors) is conducted to ascertain an optimal configuration tailored to the specific dataset.

Hyper parameter Tuning: Fine-tuning of additional hyper parameters of the KNN algorithm, including the distance metric and weighting schemes, is undertaken to optimize the model's performance. Employing cross-validation techniques aids in assessing the model's generalization ability and robustness.

Impact Evaluation: Systematic variations in charging and discharging capacity within the dataset are introduced to assess their impact on estimation accuracy. Comprehensive analysis is conducted to discern how alterations in these parameters influence the robustness and reliability of the proposed method.

Testing and Validation: The trained model is rigorously evaluated on the reserved testing dataset to validate the effectiveness of the proposed method in estimating the Li-Ion battery's State of Health. Appropriate metrics, such as accuracy, precision, and recall, are employed to quantitatively assess the model's performance and reliability.

SOH Estimation Approaches: There are 3 approaches to estimate the SOH of the batteries – direct measurement, model-based and data-driven methods.

Direct Measurement Approach: The direct measurement approach uses variables such as internal resistance, impedance, open circuit voltage (OCV) and charge/discharge current to estimate the battery SOH. Although these approaches are usually less computationally complex, they are either time consuming or they are not directly provided by the BMS as mentioned in , making them unsuitable for online estimation.

Model-Based Approach: In model-based approach, electrochemical models (EM) are used to model chemical and physical aging mechanisms of the battery using a series of non-linear and partial differential equations. To estimate the SOH of the battery, the amount of cyclable.Li-ions in the electrodes is calculated, taking into account multiple factors depending on its complexity, such as the loss of Li-ions due to the growth of the Solid Electrolyte Interface (SEI). However, these models are simplified and may not be able to reflect the changes in SOH that the battery faces in real-time.

Data-Driven Approach: Data-driven methods work by fitting huge amounts of past experimental data of key HIs and their associated SOH to predict the SOH of the battery. These could be provided by the BMS in real time, allowing for online estimation as opposed to direct measurement approach. It also does not require any information on the aging mechanisms of the Li-Ion battery, allowing it to make more complex mapping between the HIs and SOH that are not picked up by EMs.

II. LITERATURE SURVEY

2.1 State-of-Charge Estimation for Li-Ion Batteries: A More Accurate Hybrid Approach

Modeling of battery energy storage systems used for applications, such as electric vehicles and smart grids, emerged as a necessity over the last decade and depends heavily on the accurate estimation of battery states and parameters. Depending on the battery-cell type and operation, a combination of algorithms is used to identify battery parameters and define battery states. This paper deals with robust Li-ion batteries modelling with a specific focus on a hybrid approach for a more accurate state-of-charge (SOC) estimation. The analysis presents a detailed description of the state-of-the-art stand-alone SOC estimation methods and focuses on a hybrid SOC estimation technique to improve accuracy under varying conditions. Emphasis is given on performance improvements of the proposed hybrid approach compared to the conventional methods, whereas a thorough experimental validation is presented to evaluate the accuracy of the proposed method.

2.2 Effect of Temperature on the Aging rate of Li Ion Battery Operating above Room Temperature

Temperature is known to have a significant impact on the performance, safety and cycle lifetime of lithium-ion batteries (LiB). However, the comprehensive effects of temperature on the cyclic aging rate of LiB have yet to be found. We use an electrochemistry-based model (ECBE) here to measure the effects on the aging behavior of cycled LiB operating within the temperature range of 25 °C to 55 °C. The increasing degradation rate of the maximum charge storage of LiB during cycling at elevated temperature is found to relate mainly to the degradations at the electrodes and that the degradation of LCO cathode is larger than graphite anode at elevated temperature. In particular, the formation and modification of the surface films on the electrodes as well as structural/phase changes of the LCO electrode, as reported in the literatures, are found to be the main contributors to the increasing degradation rate of the maximum charge storage of LiB with temperature for the specific operating temperature range. Larger increases in the Warburg elements and cell impedance are also found with cycling at higher temperature, but they do not seriously affect the state of health (SoH) of LiB as shown in this work.

2.3 Review on Health Management System for Lithium-Ion Batteries of Electric Vehicles

The battery is the most ideal power source of the twenty-first century, and has a bright future in many applications, such as portable consumer electronics, electric vehicles (EVs), military and aerospace systems, and power storage for renewable energy sources, because of its many advantages that make it the most promising technology. EVs are viewed as one of the novel solutions to land transport systems, as they reduce overdependence on fossil energy. With the current growth of EVs, it calls for innovative ways of supplementing EVs power, as overdependence on electric power may add to expensive loads on the power grid. However lithium-ion batteries (LIBs) for EVs have high capacity, and large serial/parallel numbers, when coupled with problems like safety, durability, uniformity, and cost imposes limitations on the wide application of lithium-ion batteries in EVs. These LIBs face a major challenge of battery life, which research has shown can be extended by cell balancing. The common areas under which these batteries operate with safety and reliability require the effective control and management of battery health systems. A great deal of research is being carried out to see that this technology does not lead to failure in the applications, as its failure may lead to catastrophes or lessen performance. This paper, through an analytical review of the literature, gives a brief introduction to battery management system (BMS), opportunities, and challenges, and provides a future research agenda on battery health management. With issues raised in this review paper, further exploration is essential.

2.4 Battery-Aware Operation Range Estimation for Terrestrial and Aerial Electric Vehicles

The range of operations of electric vehicles (EVs) is a critical aspect that may affect the user's attitude toward them. For manned EVs, range anxiety is still perceived as a major issue and recent surveys have shown that one-third of potential European users are deterred by this problem when considering the move to an EV. A similar consideration applies to aerial EVs for commercial use, where a careful planning of the flying range is essential not only to guarantee the service but also to avoid the loss of the EVs due to charge depletion during the flight. Therefore, route planning for EVs for different purposes (range estimation, route optimization) and/or application scenarios (terrestrial, aerial EVs) is an essential element to foster the acceptance of EVs as a replacement of traditional vehicles. One essential element to enable such accurate planning is an accurate model of the actual power consumption. While very elaborate models for the electrical motors of EVs do exist, the motor power does not perfectly match the power drawn from the battery because of battery non-idealities. In this paper, we propose a general methodology that allows predicting and/or optimizing the operation range of EVs, by allowing different accuracy/complexity tradeoffs for the models describing the route, the vehicle, and the battery, and taking into account the decoupling between motor and battery power. We demonstrate our method on two use cases. The first one is a traditional driving range prediction for a terrestrial EV; the second one concerns an unmanned aerial vehicle, for which the methodology will be used to determine the energy-optimal flying speed for a set of parcel delivery tasks.

2.1.5 Coupling Analysis and Performance Study of Commercial 18650 Lithium-Ion Batteries under Conditions of Temperature and Vibration

At present, a variety of standardized 18650 commercial cylindrical lithium-ion batteries are widely used in new energy automotive industries. In this paper, the Panasonic NCR18650PF cylindrical lithium-ion batteries were studied. The NEWWARE BTS4000 battery test platform is used to test the electrical performances under temperature, vibration and temperature-vibration coupling conditions. Under the temperature conditions, the discharge capacity of the same battery at the low temperature was only 85.9% of that at the high temperature. Under the vibration condition, mathematical statistics methods (the Wilcoxon Rank-Sum test and the Kruskal-Wallis test) were used to analyze changes of the battery capacity and the internal resistance. Changes at a confidence level of 95% in the capacity and the internal resistance were considered to be significantly different between the vibration conditions at 5 Hz, 10 Hz, 20 Hz and 30 Hz versus the non-vibration condition. The internal resistance of the battery under the Y-direction vibration was the largest, and the difference was significant. Under the temperature-vibration coupling conditions, the orthogonal table L9 (34) was designed. It was found out that three factors were arranged in order of temperature, vibration frequency and vibration direction. Among them, the temperature factor is the main influencing factor affecting the performance of lithium-ion batteries.

2.1.6 Vibration Durability Testing of Nickel Cobalt Aluminum Oxide (NCA) Lithium-Ion 18650 Battery Cells

This paper outlines a study undertaken to determine if the electrical performance of Nickel Cobalt Aluminum Oxide (NCA) 3.1 Ah 18650 battery cells can be degraded by road induced vibration typical of an electric vehicle (EV) application. This study investigates if a particular cell orientation within the battery assembly can result in different levels of cell degradation. The 18650 cells were evaluated in accordance with Society of Automotive Engineers (SAE) J2380 standard. This vibration test is synthesized to represent 100,000 miles of North American customer operation at the 90th percentile. This study identified that both the electrical performance and the mechanical properties of the NCA lithium-ion cells were relatively unaffected when exposed to vibration energy that is commensurate with a typical vehicle life. Minor changes observed in the cell‟s electrical characteristics were deemed not to be statistically significant and more likely attributable to laboratory conditions during cell testing and storage. The same conclusion was found, irrespective of cell orientation during the test

2.1.7 Multi-axis vibration durability testing of lithium ion 18650 NCA cylindrical cells

This paper presents new research to determine if the electromechanical attributes of Nickel Cobalt Aluminium Oxide (NCA) 18650 battery cells are adversely affected by exposure to vibration commensurate with that experienced by electric vehicles (EVs) through road induced excitation. This investigation applied vibration to a set of commercially available cells in six degrees of freedom (6-DOF) using a multi-axis shaker table. This method of mechanical testing is known to be more representative of the vibration experienced by automotive components, as 6 motions of vibration (X, Y, Z, roll, pitch and yaw) are applied simultaneously. Within the context of this study, cell characterisation within the electrical domain is performed via quantification of the cell‟s impedance, the open-circuit potential and the cell‟s energy capacity. Conversely, the mechanical properties of the cell are inferred through measurement of the cell‟s natural frequency. Experimental results are presented that highlight that the electromechanical performances of the 18650 NCA cells do not, in the main, display statistically significant degradation when subject to vibration representative of a typical 10-year European vehicle life. However, a statistically significant increase in DC resistance of the cells was observed.

2.1.8 Effects of Vibration on the Electrical Performance of Lithium-Ion Cells Based on Mathematical Statistics

Lithium-ion batteries are increasingly used in mobile applications where mechanical vibrations and shocks are a constant companion. There is evidence both in the academic and industrial communities to suggest that the electrical performance and mechanical properties of the lithium-ion cells of an electric vehicle (EV) are affected by the road-induced vibration. However, only a few studies related to the effects of vibration on the degradation of electrical performance of lithium-ion batteries have been approached. Therefore, this paper aimed to investigate the effects of vibration on the DC resistance, 1C capacity and consistency of NCR18650BE lithium-ion cells. Based on mathematical statistics, the method changes of the DC resistance and the capacity of the cells both before and after the test were analyzed with a large sample size. The results identified that a significant increase in DC resistance was observed as a result of vibration at the 95% confidence level, while typically a reduction in 1C capacity was also noted. In addition, based on a multi-feature quantity, a clustering algorithm was adopted to analyze the effect of vibration on cell consistency; the results show that the cell consistency had deteriorated after the vibration test.

2.1.9 Online parameter and state estimation of lithium-ion batteries under temperature effects

In this paper, a hybrid estimation technique is proposed for lithium-ion batteries. This strategy makes use of state-space observer theory to reduce the complexity of the design and the stability analysis. However, the battery's parameters knowledge is required for the state-space model, which limits the performance as the battery's parameters vary. Therefore, an online parameter identification strategy is proposed to track the parameters deviation. The stability of the closed-loop estimation scheme is guaranteed by Lyapunov's direct method. Unlike other estimation techniques where temperature effects are ignored, this paper proposes a universal compensation strategy which can be used with many estimation algorithms available in the literature. The performance of the proposed scheme is validated through a set of experiments under different currents and temperatures along with comparison against an adaptive observer.

III. System Analysis

3.1 Problem Definition

Predicting the lifespan of Li-ion batteries is crucial to safeguarding against potential damage to other healthy batteries within a connected system. Li-ion battery packs often consist of multiple cells linked together in series and parallel configurations. When one cell deteriorates or becomes damaged, it can compromise the performance and health of the entire battery pack, leading to potential safety hazards and decreased efficiency. Additionally, with the rapid growth of the market for second-use EV batteries, there is a pressing need to assess the state-of-health and performance of these batteries accurately. These used EV batteries retain a significant amount of residual capacity post-vehicle lifespan and can be repurposed for various applications, such as energy storage solutions. A data-driven analysis of the state-of-health and performance of these batteries is essential for maximizing their lifespan and optimizing their utilization in secondary applications, ensuring sustainable and efficient energy solutions.

3.2 Existing System

In most of these existing works, the raw data is transmitted to Cloud for health prediction, which increases the power needed by the transmitter. Since existing health prediction processes do not work for IoT devices deployed in the wild we have unique iThing architecture capable of performing the SOH estimation and RUL prediction on-board using peak extraction method with minimal computational load and storage requirement. The iThing architecture, the peak extraction method, the methodology used, and the correlation analysis are explained.

3.3 Proposed System

A lithium ion life estimation system consist of ATMEGA 328P as a main controller which monitors the charging and discharging status of the battery and these values are recorded and sends the data to cloud using ESP8266 Wi-Fi module. The current status of lithium ion battery is displayed through lcd display .The charging and discharging rate is stored in the form of ampere per hour .More over our system uses KNN algorithm which classifies the number of used cycles of the battery by comparing the hardware data from cloud with the existing dataset from the number of used cycle the remaining cycles and life is calculate. The project was planned on the basis that, in the future E-Vehicles will play a major part in transportation and this project can be useful for that.

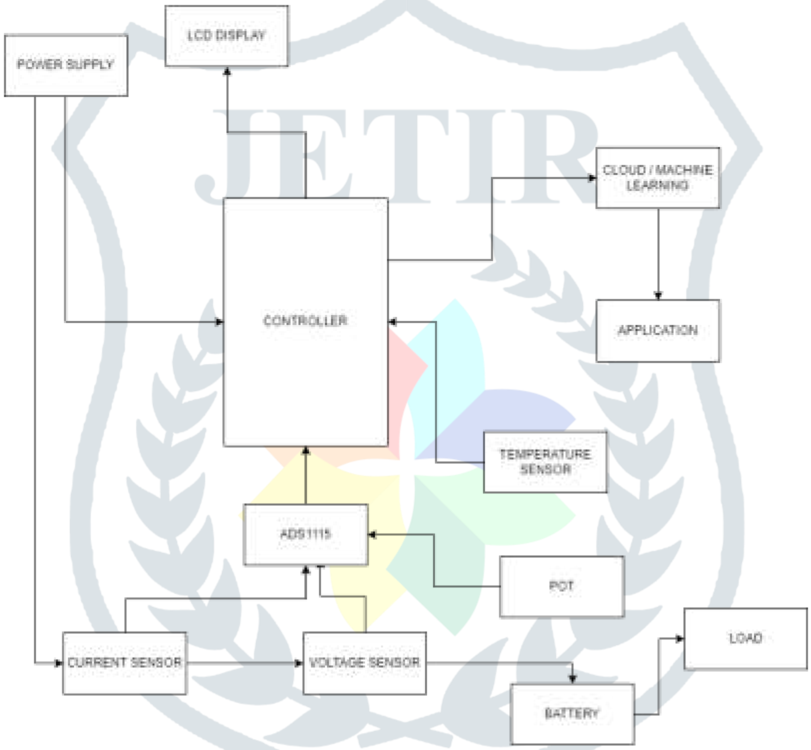

Figure 5. Block Diagram

IV. System Design

The system design for the Lithium-Ion Life Estimation System is meticulously crafted to orchestrate a seamless integration of hardware components, intelligent algorithms, and cloud services. This holistic approach aims to deliver a robust solution for monitoring and predicting the State of Health (SOH) of lithium-ion batteries, catering to the burgeoning demand for reliable energy storage solutions in diverse applications, including electric vehicles and renewable energy systems.

The architectural design serves as the cornerstone of the system, delineating the roles and interactions of key components. At its heart lies the Main Controller, powered by the ATMEGA 328P microcontroller, renowned for its low power consumption and adeptness in embedded systems applications. This controller orchestrates the intricate dance of data acquisition from sensors, decoding voltage, current, and temperature readings with precision and efficiency.

Complementing the Main Controller is the ESP8266 Wi-Fi Module, a stalwart in wireless communication, seamlessly bridging the physical realm of the system with the boundless expanse of cloud services. Through its prowess, the system effortlessly communicates vital battery data to cloud-based storage and analysis platforms, facilitating real-time monitoring and analysis of battery performance.

An integral facet of the system's user interface is the LCD Display, a beacon of clarity and accessibility. This display provides users with intuitive access to real-time battery status information, including voltage, current, temperature, and the all-important SOH estimation. Its ergonomic design ensures that users can effortlessly glean insights into battery health with a glance, fostering informed decision-making and proactive maintenance.

The selection of sensors is a testament to the system's commitment to accuracy and reliability. Meticulously chosen for their precision and fidelity, voltage and current sensors serve as the eyes and ears of the system, faithfully capturing the nuances of charging and discharging dynamics with unparalleled accuracy. The data flow within the system orchestrates a symphony of information, seamlessly traversing from acquisition to analysis:

4.1 Data Acquisition: The Main Controller dutifully gathers voltage, current, and temperature data from sensors, imbuing the system with a keen awareness of the battery's physical state.
4.2 Data Processing: Armed with raw sensor data, the Main Controller deftly computes charging and discharging rates, harnessing the power of the KNN algorithm to distill nuanced observations into actionable insights.
4.3 Data Transmission: Through the ESP8266 Wi-Fi Module, the system embarks on a journey to the cloud, transmitting processed data and SOH estimations with unwavering fidelity.
4.4 Cloud Analysis: Nestled within the cloud, the transmitted data finds sanctuary, fueling the fires of analysis and prediction. Here, the KNN algorithm unfurls its magic, unraveling the mysteries of battery life with unparalleled precision and foresight.
In conclusion, the system design of the Lithium-Ion Life Estimation System is not merely a collection of components; it is a testament to ingenuity and innovation. Through the seamless integration of hardware, wireless communication, and cloud-based intelligence, the system heralds a new era of battery management, empowering users with actionable insights and paving the way for a future fueled by sustainable energy solutions.

V. System Implementation

The process involved in estimating the State of Health (SOH) of lithium-ion (Li-ion) batteries using data-driven methods, particularly focusing on a partial charge and discharge current sequence fed into the K-Nearest Neighbors (KNN) algorithm, can be broken down into several steps. Let's go through each step elaborately:

5.1. Data Collection: The first step involves collecting relevant data related to the behavior and performance of the Li-ion batteries. This data could include parameters such as voltage, current, temperature, and charging/discharging cycles. It's essential to gather a diverse range of data to ensure the model captures various scenarios and conditions that the battery might encounter.
5.2. Feature Extraction: Once the data is collected, the next step is to extract meaningful features from it. Feature extraction involves identifying and selecting relevant attributes or parameters that can serve as strong health indicators (HIs) for estimating the SOH of the battery. In this case, the partial charge and discharge current sequence is proposed as a strong health indicator.
5.3. Data Preprocessing: Before feeding the data into the machine learning model, it needs to be preprocessed to ensure its quality and compatibility with the algorithm. This step may involve tasks such as removing outliers, handling missing values, normalizing the data, and splitting the dataset into training and testing sets.
5.4. Model Selection: The choice of the machine learning algorithm plays a crucial role in the accuracy and effectiveness of the SOH estimation. In this project, the K-Nearest Neighbors (KNN) algorithm is selected due to its fast learning speed, simplicity, and good generalization properties. KNN is a supervised learning algorithm used for classification and regression tasks.
5.5. Training the Model: With the preprocessed data and selected algorithm, the next step is to train the machine learning model. During training, the model learns the relationship between the input features (partial charge and discharge current sequence) and the target variable (SOH). The KNN algorithm, in particular, works by finding the K-nearest data points in the training set to the input data point and predicting the output based on a simple voting mechanism or weighted averaging.
5.6 Parameter Tuning: Fine-tuning the parameters of the KNN algorithm, such as the number of neighbors (K), is crucial to optimize the model's performance. This step may involve techniques like cross-validation to find the best hyperparameters.
5.7. Evaluation: Once the model is trained and tuned, it needs to be evaluated to assess its performance and generalization capability. This is typically done using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or R-squared (R2) score. The model is tested using a separate test dataset that was not used during training.
5.8. Validation and Optimization: The proposed method is tested with an open dataset to validate its effectiveness. The results are analyzed to determine how accurately the model estimates the SOH of the batteries. Additionally, the impact of selecting different charging and discharging capacities on the estimation accuracy is comprehensively evaluated.
5.9. Comparison and Conclusion: Finally, the results of the proposed data-driven method are compared with other existing methods for SOH estimation. The advantages and limitations of each method, particularly in terms of real-time automotive compatibility and hybrid electric applications, are discussed. Insights gained from the study can be used to further refine the methodology and improve future battery management systems.
5. 10. Methodology:
KNN Algorithm
In the process of estimating the State of Health (SOH) of lithium-ion batteries using the K-Nearest Neighbors (KNN) algorithm, several steps are involved. Initially, the dataset is prepared, comprising various battery performance metrics like voltage, current, temperature, and charging/discharging cycles. From this dataset, the partial charge and discharge current sequence is singled out as the primary feature for SOH estimation. The SOH itself serves as the target variable that the algorithm seeks to predict based on this feature. Before proceeding, normalization of the input features is conducted to ensure uniformity in scale. Subsequently, the KNN algorithm is trained on the prepared dataset, storing training instances for future reference. When predicting the SOH of a new data point, the algorithm calculates distances to all other points in the training set and selects the K-nearest neighbors. Depending on the task, either a simple averaging or a weighted averaging of these neighbors' SOH values is used to predict the SOH of the new data point. Following prediction, the model's performance is evaluated using metrics such as Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE). Parameter tuning, particularly adjusting the number of neighbors (K), is essential for optimizing the algorithm's performance. The implemented KNN algorithm is then validated using an open dataset to assess its effectiveness in SOH estimation, with subsequent analysis informing adjustments to the algorithm or parameters as needed. Overall, while KNN offers simplicity and accuracy, meticulous data preprocessing and parameter tuning are necessary for optimal results. The K-Nearest Neighbors (KNN) algorithm operates on the principle of similarity, where it predicts the label or value of a new data point by considering the labels or values of its K nearest neighbors in the training dataset.

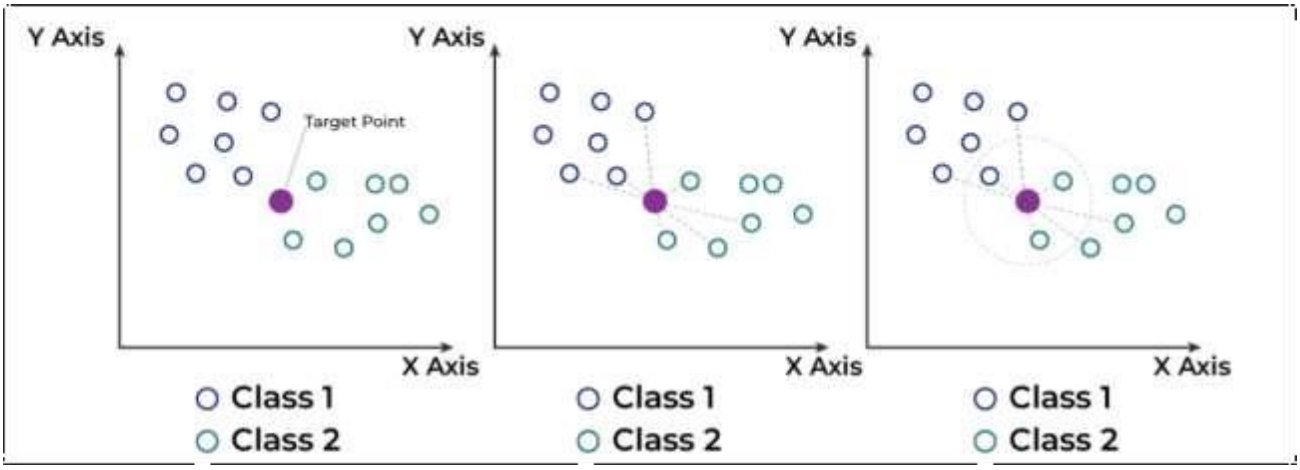

Figure 12.Working of KNN Algorithm

Step-by-Step explanation of how KNN works is discussed below:

Step 1: Selecting the optimal value of K

K represents the number of nearest neighbors that needs to be considered while making prediction.

Step 2: Calculating distance

To measure the similarity between target and training data points, Euclidean distance is used. Distance is calculated between each of the data points in the dataset and target point.

Step 3: Finding Nearest Neighbors

The k data points with the smallest distances to the target point are the nearest neighbors.

Step 4: Voting for Classification or Taking Average for Regression

In the classification problem, the class labels of are determined by performing majority voting. The class with the most occurrences among the neighbors becomes the predicted class for the target data point.

In the regression problem, the class label is calculated by taking average of the target values of K nearest neighbors. The calculated average value becomes the predicted output for the target data point.

The algorithm selects the K data points from X that have the shortest distances to x. For classification tasks, the algorithm assigns the label y that is most frequent among the K nearest neighbors to x. For regression tasks, the algorithm calculates the average or weighted average of the values y of the K nearest neighbors and assigns it as the predicted value for x.

Advantages of the KNN Algorithm

- **Easy to implement** as the complexity of the algorithm is not that high.
- **Adapts Easily** – As per the working of the KNN algorithm it stores all the data in memory storage and hence whenever a new example or data point is added then the algorithm adjusts itself as per that new example and has its contribution to the future predictions as well.
- **Few Hyperparameters** – The only parameters which are required in the training of a KNN algorithm are the value of k and the choice of the distance metric which we would like to choose from our evaluation metric.

Disadvantages of the KNN Algorithm

- **Does not scale** – As we have heard about this that the KNN algorithm is also considered a Lazy Algorithm. The main significance of this term is that this takes lots of computing power as well as data storage. This makes this algorithm both time-consuming and resource exhausting.
- **Curse of Dimensionality** – There is a term known as the peaking phenomenon according to this the KNN algorithm is affected by the curse of dimensionality which implies the algorithm faces a hard time classifying the data points properly when the dimensionality is too high.
- **Prone to Overfitting** – As the algorithm is affected due to the curse of dimensionality it is prone to the problem of overfitting as well. Hence generally feature selection as well as dimensionality reduction techniques are applied to deal with this problem.

VI. RESULTS AND DISCUSSION

The provided data presents the charging and discharging characteristics of a lithium-ion battery over multiple cycles, along with corresponding voltage and temperature readings. For instance, during charging, the voltage decreases from 12.2V to 79.6V over 150 cycles, with a simultaneous increase in temperature from 28.0°C to 32.3°C. Conversely, during discharge, the voltage drops from 3.2V to 79.3V over the same cycle count, while the temperature rises from 28.2°C to 37.2°C. These observations highlight the dynamic behavior of the battery during charge and discharge cycles. Additionally, the comparison with the kNN model's predictions suggests a close alignment between the experimental results and the model's estimations, indicating the model's effectiveness in predicting state-of-charge (SOC) based on the provided features.

Charging	Time[Min]	Voltage[V]	Temperature[°C]
10 Cycles	89.3	12.2	28.0
50 Cycles	85.6	12.2	29.2
100 Cycles	82.8	12.2	31.1
150 Cycles	79.6	12.2	32.3
Discharging	Time[Min]	Voltage[V]	Temperature[°C]
10 Cycles	88.7	3.2	28.2
50 Cycles	85.0	3.2	30.3
100 Cycles	81.2	3.2	33.1
150 Cycles	79.3	3.2	37.2

FIG. 3. COMPARISON OF SOC WITH EXPERIMENT AND KNN MODEL IN BATTERY DURING CHARGE: (A) EXPERIMENT RESULT, (B) 10 CYCLES, (C) 50 CYCLES, (D)100 CYCLES, (E) 150 CYCLES.

VII. CONCLUSION

The lifetime of Li-ion batteries is the key challenge to achieve sustainable battery performance. The application specific usage dominates the degradation path, and an accurate aging prediction is still a challenge. The precise forecasting of the battery life has a far-reaching consequence, which can help to understand the battery behavior under certain circumstances and perform diagnosis accordingly. In this project work, several techniques are developed following different methodologies, and model performances are compared with each other. The assessment is validated by using a common training dataset and tested/simulated on completely new cells.

VIII. FUTURE ENHANCEMENTS

The capacity fading rate was also found to be possibly related to the frequency and duration of resting periods, and more experiments are required to confirm this effect. Additionally, more cycle life experiments are needed with different initial SoCs and ΔDoDs improve t he capacity fading model. The capacity fading results obtained were all based on usage of the cells, and calendar losses has not been considered. However, most of the time an EV is not being driven, and calendar losses cannot be simply ignored. More investigation is requir ed on the correlation between calendar and cycling losses of the capacity. The empirical equations of the internal cell impedance are determin ed with a unidirectional current; the validity of the equations has to be confirmed for changing current directions in a dynamic profile. Furthermore, the ohmic resistance was found to be varying with cycling of the cells. Unfortunately, the variations did not show a tr end and the resistance rise could not be modelled. Additional experiments are required to investigate whether the variations are caus ed by regenerative braking and to model the ageing dependence of the ohmic resistance with various stress factors.

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