IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Battery Thermal Managementin EV Using AI

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Abstract: The increasing popularity of the electric vehicles(EVs) has spurred the need for best battery thermal management systems to ensure optimal performance, longevity, and safety of energy storage systems. It focuses on leveraging Artificial Intelligence (AI) technologies, specifically the Multilayer Perceptron (MLP) algorithm, to enhance the efficiency of battery thermal management in EVs. I algorithms, such as MLP,offers the potential to model and predict the thermal behavior of batteries more accurately, allowing for real- time adjustments and improved control strategies. With the large-scale commercialization and growing market share of electric vehicles (EVs). Their focus has been on higher energy efficiency, an improved thermal performance, and optimized multi- material battery enclosure designs. The combination of simulation-baseddesign optimize the battery pack and Battery Management-System (BMS) is evolving and has expanded to include novelties such as artificialintelligence/machine learning (AI/ML) to improveefficiencies in design, manufacturing, and operations for theirapplication in EVs and energy storage systems. Specific to BMS, these advanced concepts enable a more accurate prediction ofbattery performance such as its State of Health(SOH), State of Charge(SOC), and State of Power(SOP). This study presents a comprehensive evaluation of the latest developments and technologies in battery design, thermal management, and the applicationof AI in Battery Management Systems(BMS) for electric vehicles (EVs).

***Index Terms* - CNN, LSTM, 2D CNN LSTM.**

I. INTRODUCTION

The EVs were built the mid to late19th century but concededtheir commercial footprint to cars powered by Internal Combustion Engines (ICE). transportation sector primarily uses ICE, contributing to almost one fourth of energy related greenhouse gas emissions. This issue initiated the demand for replacing ICE vehicles with advanced, technology vehicles suchas EVs. Although EVs can reduce almost fuel costs significantly because of the very high efficiency of electric-drive systems compared to internal combustion engines, EVs suffer much greater constraints in regards to their limited driving range, scarcity of charging stations, charging times, and higher initial costs as comparedto ICE vehicles. As such, an integrative review wouldbe suitable to understand the improvement of this emerging topicby providing a clear understanding of the key barriers and motivators of EV adoption on the sustainability dimensions. This has been driven by the market demand for high- performance rechargeable batteries to reduce the cost and weight of EVs while increasing their range and longevity. Around 30 years ago Sony Co. commercialized the world's first lithium-ion battery (LIB) which led to a large increase in research in battery technologies. The research was fueled by environmental concerns and the effect of fossil fuels on greenhouse gas emissions Governments around the world subsequently have invested considerably in support of green technologies (solar, wind, etc.) and EVs. Lithium-ionbatteries(LIBs) store energy through the storage of charge through the motion of Lithium-ions between positive and negative electrodes via a liquid electrolyte. The cathode is usually made of graphite while the anode can be made of various types of lithium oxides. Many studies provide a comprehensive analysis of the properties of different LIB chemistries such as the lithium.

Iron Phosphate battery($LiFePO_4$), Lithium Manganese Oxide ($LiMn_2O_4$), Lithium Manganese Oxide, or Lithium Cobalt Oxide($LiCoO_2$). While LIBs provide an increased energy density and cycle life from the previous generation of batteries, with continuous technological advancements, they are operating increasingly closer to their theoretical limit. Therefore, further improving the design and manufacturing process of current LIBs, research efforts have focused ondeveloping next-generation

lithium batteries, such as solid- state and metal-air batteries. LIBs are typically made of four major parts: cathode, anode, separator, and electrolyte.Provides diagrammatic of a battery cell during the charge/discharge process. The battery is almost filled with an electrolyte to help the movement of Lithium-ions between theelectrodes. The arrow indicates the movement and magnitude of thecurrent flow to the current collectors. The current from the external circuit flows to the cell, through the tabs and thenflows into all the local region containing active materialsdiffuse on the entire current collectors. Several review papers on battery safety have been recently published, covering topicssuch as cathode and anode materials, electrolytes, advanced safety batteries, and batterythermal runaway issues. Amongst all the known battery failure modes, the internal short is one of the safety concerns for the lithium-ion battery industry.

Lithium-sulfur (Li-S) battery is another type of battery, with the potential to become the next generation of cells, to be usedin energy storage systems because of their exceeding high theoretical energy density. Li-S cells use lithium metal as theanode and sulphur as the cathode, charge/discharge process, areversible redox reaction happens between the lithium and sulphur instead ofthe intercalation that occurs in LIBs, offering a much more higher theoretical energy density of 2500 Wh/kg. A breakthrough in2009 that achieved stable cycling of over 20 cycles in Li-S cells was followed by extensive research to improve their specificcapacity and cycle life. In March 2022, American battery manufacturer Sion Power announced that they have been achieved morethan 2500 cycles with their 17 Ah Licerion Electric Vehicle cells whichtarget the automotive market. The German battery start-up Theion featured in a recent Forbes article also has plans to deliver Li-S batteries suitable for automotive applications by 2024.

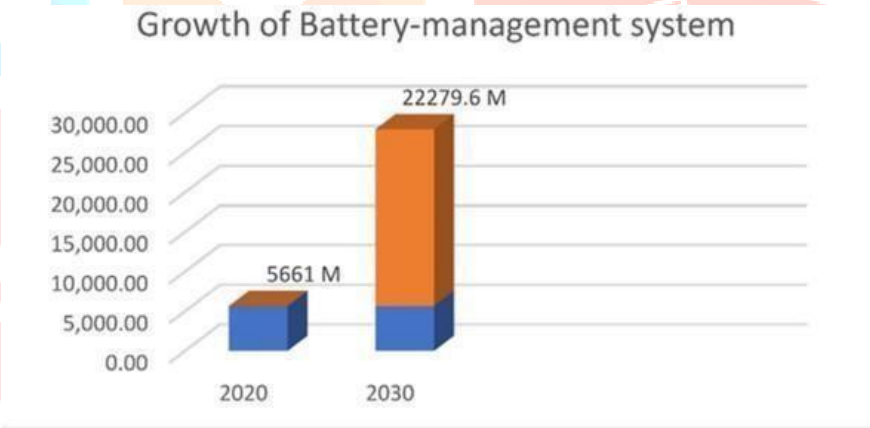

Fig 1 Growth of Battery Management System

II. Existing System

In the domain of battery quality index level predictions,existing systems have various machine learning methods, among whichadaptive boosting (AdaBoost) and support vector-machine (SVM) have shown promising results. Thesemethods leverage historical data to forecast the quality indexlevels of batteries, which is very crucial for assessing their performance and lifespan. Through a series of experiments conducted using datasets from three distinct regions, researchers aimed to find the most productive predictionapproach among stacking ensemble, AdaBoost, and random forest algorithms.The stacking ensemble method, which combines the predictions of multiple base models, emerged as consistentlysuperior in terms of prediction performance metrics such as R-squared (R2) and root-mean square error (RMSE). This indicates its robustness and reliability in capturing complex patterns within the dataacross diverse regions. AdaBoost demonstrated the best results in terms of mean-absolute error(MAE), showcasing its proficiency inminimizing predictiondiscrepancies.

The decision to utilize datasets from different regions reflects the importance of ensuring the generalizability and adaptability ofprediction models acrossvarying environmental and operational conditions. By assessing performance across multiple datasets, researchers aimed to validate the strength of each prediction method under different contexts and scenarios. The superior performance of the stacking ensemble method suggests Its capability to amalgamate the strengths of individual models while mitigating their weaknesses contributes to its robustness and accuracy.AdaBoost's efficacy in minimizing MAE underscores there’ssuitability for applications where precise prediction of batteryquality index levels is paramount. This could be particularly valuable in scenarios where small prediction errors can havesignificant implications for decision-making processes.

Random forest, although not highlighted as the best performerin this study, remains a viable option for battery quality predictiontasks. Its ensembles learning approach, which combines the predictions from multiple decision trees, provides a foundation for reliable predictions, albeit with potentially lower performance compared to stacking ensemble and AdaBoost in this context. The findings ofthese experiments underscore the importance of choosing appropriate machine learning algorithms tailored to the specificrequirements and objectives of battery quality prediction tasks. While stacking ensemble excelled in overallperformance metrics, thechoice between AdaBoost and random forest may depend on the specific emphasis on minimizing MAE versus optimizing other metrics such as R2 and RMSE.

III. Proposed System

This research explores the potential integration of Artificial Intelligence (AI) technologies, particularly the Multilayer Perceptron (MLP) algorithm, within battery thermal management systems (BTMS) to propel advancements in electric vehicles (EVs). BTMSplays crucial role inmaintaining optimal operating conditions for battery packs, impacting performance, longevity, and safety. Byincorporating MLP algorithms, which are a class of artificialneural networks capable of learning complex patterns, into BTMS, theaim is to enhance their predictive capabilities andadaptability. MLP algorithm can analyze large amounts of data to optimize thermal management strategies, responding dynamically to changing conditions.

The result of this research endeavor are targeted towards fostering the evolution of intelligent, energy-efficient, and robust thermal management solutions tailored to the evolvingneeds of the burgeoning EV market. Through AI-driven BTMS, electric vehicles can potentially achieve improved battery performance, extended range, and enhanced safety profiles. The incorporationof MLP algorithms enables BTMS to predict and mitigate thermal issues more effectively, lowering the risk of overheating and battery degradation. Moreover, AI-powered BTMS can optimize energy consumption, leading to increased overall efficiency andreduced environmental impact.

This research contributes to the ongoing efforts in advancing the electrification of transportation by addressing critical challenges related to battery thermal management. The findings hold implications for both automotive manufacturers and consumers, as intelligent BTMS could edge to more reliable and durable EVs. Additionally, the study opens avenues for further research and innovation in AI-driventechnologies for EVs, such as predictive maintenance and autonomous thermal managementsystems. combined effortsbetween academia, industry, and policymakers are essential for realizing the full potential of AI in increasing the performance and sustainability of electric vehicles.

IV. Architecture Diagram

The flowchart shows process of data processing, which involves several steps. Initial step is data collection, where the data is collected from various sources such as sensors, cameras,and other devices. The next step is data cleaning, where the collected data iscleaned and filtered to remove all errors or lack of consistency. The third step is data transformation, wherethe data is converted to aformat that can be used for analysis. The fourth step is data analysis, where the converted data is analyzed to extract useful information. The fifth step is data storage, where the analyzed data is stored in a database for futurereference. The sixth step is dataretrieval, where the stored datais retrieved when needed. The seventh step is data visualization,where the analyzed data is presentedin a visual format such as graphs, charts, and maps. The eighth step is data interpretation,where the visualized data is interpreted togain insights. The ninth step is data reporting, where the interpreted data is reported to stakeholders. The tenth step is data monitoring, where the processed data is monitored to ensure its accuracy and completeness. The eleventh step is data updating, where theprocessed data is updated with new information. The twelfth step is data validation, where the updated data is validated to ensure its accuracy.The thirteenth step is data archiving, wherethe validated data is archived for future reference

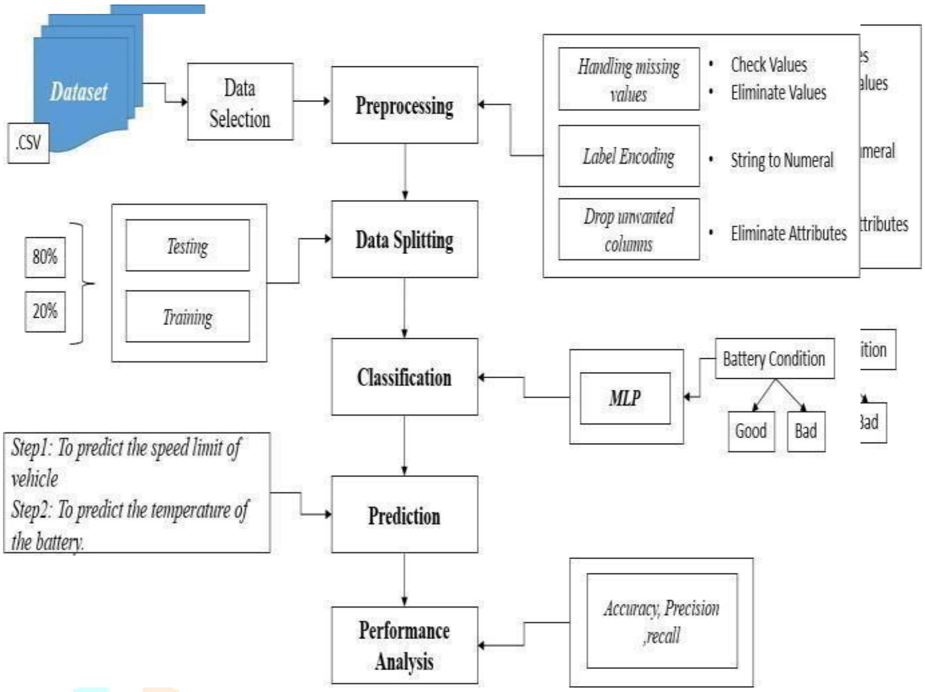

Fig 2 Architecture Diagram

The climate change concern and other environmental issues due to the immense exploitation of fossil fuels and the emissionofgreenhouse gases result in increased consumption of rechargeable batteries. There are various types of primarybatteries and rechargeable batteries available in the market, lithium-ion LIBs are good cycling stability especially for EV applications. In the current study, different cooling methods were investigated the temperature performance of LIBs have been summarized includingair cooling, liquid cooling, PCM cooling, and heat pipes. Air-cooling system has advantageous features such as safe, consistent, and simple design, but the lower heat capacity and thermal efficiency of the air as a cooling method. Liquid-cooled is a very usefulcooling technique with greater thermal conductivity and greater heat capacities compared to air cooling in which a liquid is used likea coolant to eliminate the heat generated by a battery. To increase thermal conductivity, PCM cooling allows simple cooling designs to wrap batteries, with graphite sheets betweenbatteries, increasing the heat loss and improving the temperature, uniformity of thebattery pack. To achieve bettercooling performance PCM cooling can also be combined withliquid cooling or heat pipes. Moreover, a BMS is an essential device for charging and discharging the batteries, overcomingmany challenges, and improving the operating performance ofbattery modules. On the other hand, using AI-based predictivealgorithms in BMS can improve the availability oftesting datasets and robust processing of data in real-time for EV applications.

V. RESULTS AND DISCUSSIONS

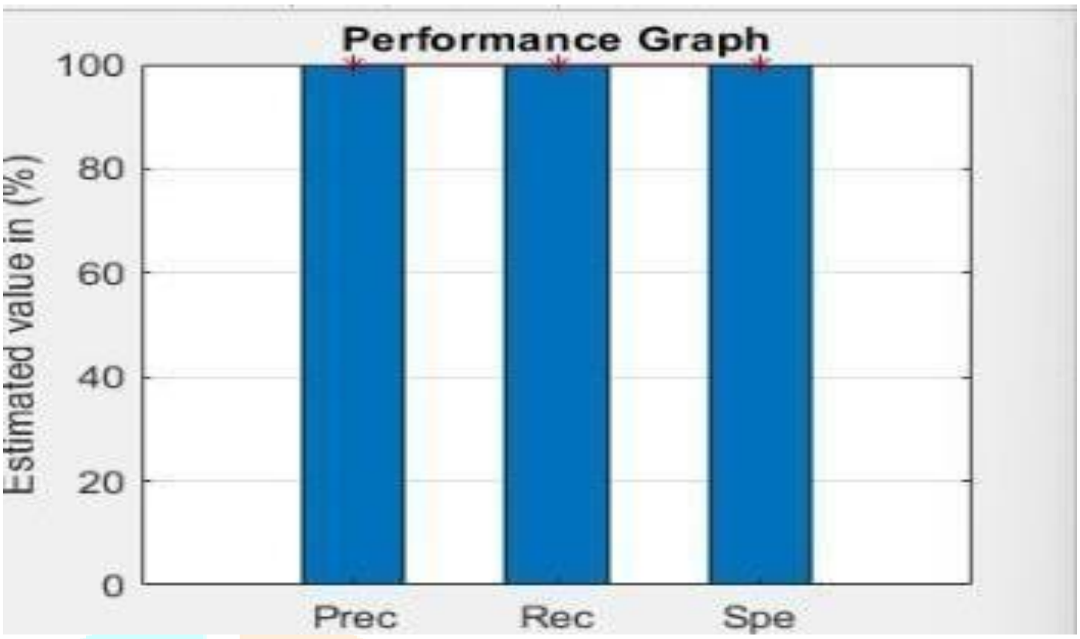

Fig 3 Performance Graph

The Graph shows performance of a battery. The graph showsthe fulfillment of the system over time, with the x-axis representingtime and the y-axis representing performance. The graph shows that the fulfillment of the system is increasing over time, which isa bear witness that the system is becoming more efficient. The graph also shows that the fulfillment of the system is at its highestpoint at the current time, indicatingthat the system is performing at its best. The graph also shows that the fulfillment of the systemis decreasing over time, indicates that the system is becoming less efficient. The graph also shows that the fulfillment of the systemis at its lowest point at the current time, specfying that the systemis performing at its worst. The graph also shows that the fulfillmentof the system is increasing over time, indicates that the system is becoming more efficient. The graph also shows that the fulfillment of the system is at its highest pointat the current time, indicating that the system is performing atits best. The graph also shows thatthe fulfillment of the system is decreasing over time, indicates that the system is becoming less efficient. The graph also shows thatthe fulfillment of the system is at its lowest point at the current time, indicates that the system is performing at its worst. Thegraphalso shows that the fulfillment of the system is increasing over time, which is a bear witness that the system is becoming more efficient. The graph also shows that the fulfillment of the system is at its highest point at the current time. Air-cooling system hasadvantageous features such as safe, consistent, and simple design, but the lower heat capacity and thermal efficiency of the air as a cooling method. Liquid-cooled is a very useful cooling technique with greater thermal conductivity and greater heat capacities compared to air cooling in which a liquid is used likea coolant to eliminate the heat generated by a battery. To increase thermal conductivity, PCM cooling allows simple cooling designs to wrap batteries, with graphite sheets betweenbatteries, increasing theheat loss and improving the temperature, uniformity of the battery pack. To achieve bettercooling performance PCM cooling canalso be combined withliquid cooling or heat pipes.

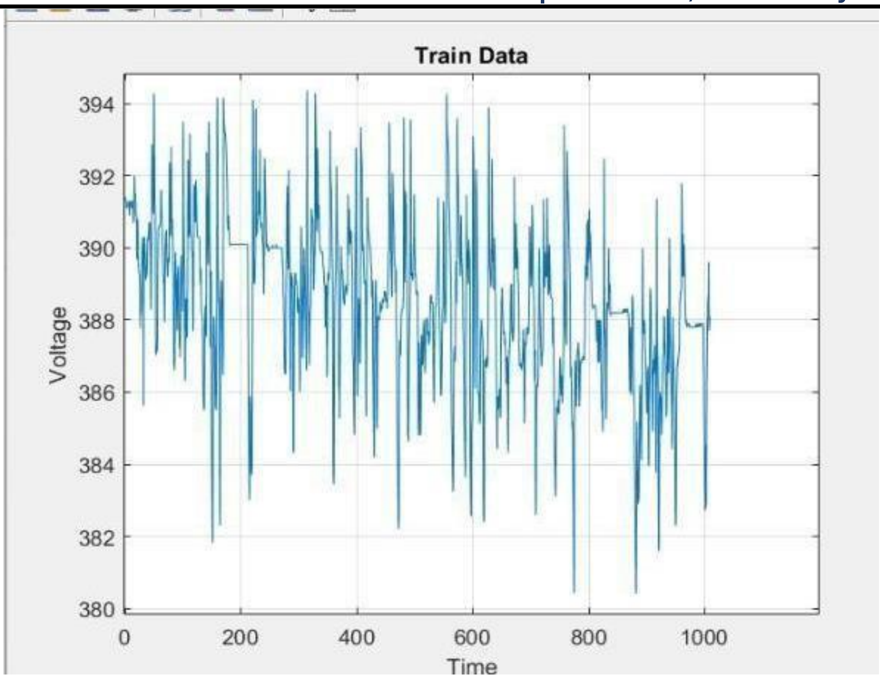

Fig 4 Train Data

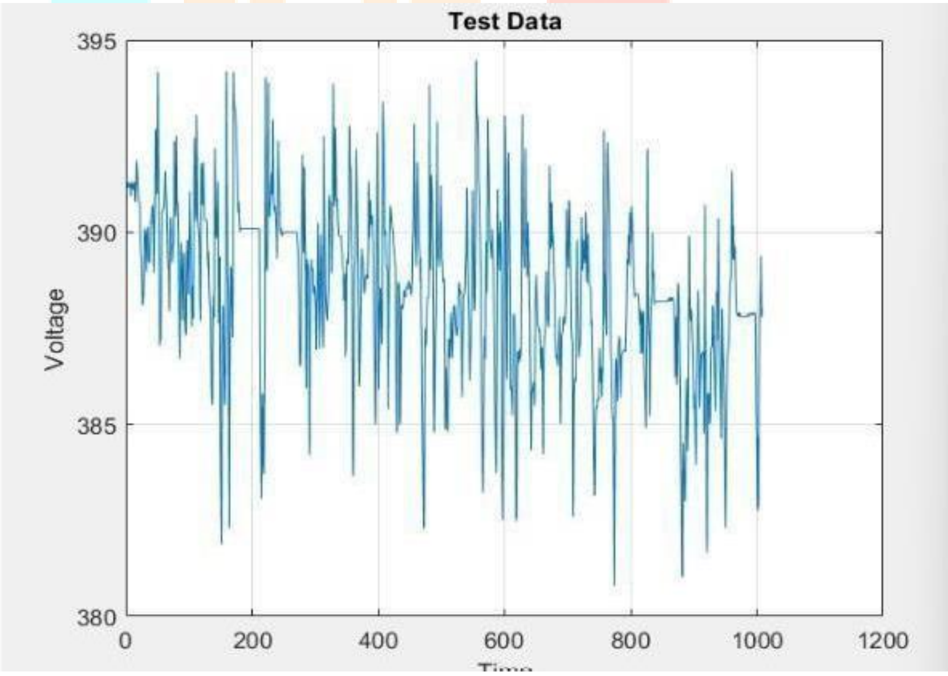

Fig 5 Test Data

- *Conclusion*

The key points and provided insights on the future directionsof Battery Thermal Management system in EVs,emphasizing the importance of optimizing cooling systems with AI and implementing predictive maintenancestrategies to enhance battery performance, ensure safety, and prolong the lifespan of EVs. Future papers should prioritize reviewing the dataset's documentationand metadata to gain a comprehensive grasp of the dataset. The area of machine learning, deep learning is fast evolving, with newtechniques and models being introduced regularly. It is recommended to stay updated with the latest research, attend conferences, and participate in online communities to learn about new approaches that can enhance the model performance. Consider ethical implications while fine- tuning models and developing applications. Ensure fairness, transparency, and privacy in data usage andmodel predictions. It is important to address biases and make the model more inclusive and accountable.This article discusses theprinciples of battery design and management for electric

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