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An Analytical Research on Machine Learning-based Battery Management Systems

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Abstract

Global warming and global pollution can consequence in many severe changes to the environment, ultimately challenging environmental problems and impacting human health. Human activities that result in an electronic-based population are the primary causes of the sharp rise in waste, particularly battery waste. Massive releases of heavy metals from battery waste impact health and ecosystems as a whole. Hence there is need to work on battery lifecycle and its affecting measuring factors. However, there are many challenges to enhance the lifecycle of battery and to sustain environmental balance. Machine learning is a form of artificial intelligence that is fundamentally present in almost every area of our lives. It increased automation and increased productivity. This research article provides an overview of exemplary research efforts for efficient Machine Learning-based Battery Management Systems (BMS) to improve battery life cycles and address their measurement factors in the context of ecological development.

Keywords— *battery lifecycle, measuring factors, Artificial Intelligence, BMS, Machine Learning, RUL.*

INTRODUCTION

Machine learning is a form of artificial intelligence that is fundamentally present in almost every area of our lives. It increased automation and increased productivity. This research article provides an overview of exemplary research efforts for efficient Machine Learning-based Battery Management Systems (BMS) to improve battery life cycles and address their measurement factors in the context of ecological development. This article covers the design and synthesis of battery materials along with recent advances in the field of machine learning Furthermore, this review article also covers future lines of potential research and development directions for Machine Learning techniques like clustering and regression in theprocess of determining battery lifetime. Global warming and global pollution can consequence in many severe changes to the environment, ultimately challenging environmental problems and impacting human health. Human activities that result in an electronic-based population are the primary causes of the sharp rise in waste, particularly battery waste. Massive releases of heavy metals from battery waste impact health and ecosystems as a whole. Hence there is need to work on battery lifecycle and its affecting measuring factors. However, there are many challenges to enhance the lifecycle of battery and to sustain environmental balance. The world's climate has deteriorated sharply in recent decades due to rapid increases in global temperatures caused by conventional energy sources and CO2-emitting fossil fuel vehicles. It emphasizes the effects on food security, land and marine ecosystems, migration and displacement, and socioeconomic development. Energy storage system research and development have been initiated by this. Lithium-ion (Li-Ion) has emerged as one of the most relevant and widely used solutions in the development of energy storage devices, widely used in low-power portable electronic devices, electric vehicle power supplies, and grid-scale energy storage. One of the most significant pieces of technology that has transformed the portable electronics and electric vehicle sectors today is Li-ion batteries. The most important characteristics of lithium-ion batteries include safety, long life, low self- discharge, high energy density, and high power density, and high-power density, which make it superior to other battery types like lead-acid and sodium sulfur (NaS). Lithium-ion batteries are the most widely used power batteries due to their obvious advantages of high voltage, low self- discharge rate, long life and high safety performance. Lithium-ion batteries are considered the most promising energy source due to their large capacity and high energy density. The main power source of new energy vehicles, Li-ion Batteries, has a long history of use in the automotive, aviation, and other industrial sectors. Rechargeable battery use in electric vehicle applications has grown in popularity recently Consequently, a recent study has revealed a 168% spike in Electric vehicles sales in India in 2021 compared to 2020. The adoption of electric and alternative fuel vehicles has

undoubtedly risen due to increased understanding of their economic and environmental advantages, and this will also help the
nation reach its goal of net zero emissions.

BATTERY MANAGEMENT SYSTEMS

A battery is a collection of electrochemical cells that power electrical equipment. Batteries continuously convert chemical energy into electrical energy and must be properly maintained for optimum. A soiled battery may discharge through the muck on its top case. Electrolyte, negative and positive electrodes, and battery case make up a battery. At the two spatially separated electrodes, chemical processes occur, and an external conducting circuit connecting the electrodes can provide electrical power. Electrolytes don't have much electronic transport and conduct electricity by the movement of ions. Ions and electrons are both carried by electrodes. The batteries can be raised in voltage to achieve connected in series with others, and it is required to link them in parallel to increase capacity. Primary batteries, rechargeable batteries, and fuel cells are the three main types of batteries. One or both of the electrode reactions in a main battery are irreversible, making it impossible to recharge the battery. The electrochemical reactions in a secondary battery can be turned around, allowing the battery to be recharged hundreds or even thousands of times. Reactants are continuously delivered into a fuel cell from the outside. In addition to battery usage, we use a management system with special monitoring features such as charge management mechanisms and temperature control to prevent health, safety and property risks. These systems use merit-based metrics to control battery performance. The performance and condition of the battery are estimated using data such the state-of-health (SOH) and state-of-charge (SOC). In this review article, we suggest a clever way to research the above-mentioned factors utilizing a data-driven methodology. To estimate these values, we propose a machine learning method that separates the important features from the discharge curve. Knowledge can be extracted from complex data without relying on previous underlying relationships between data variables. Numerous simulations have been proposed to assess how well the suggested approach performs in various currents and temperatures.

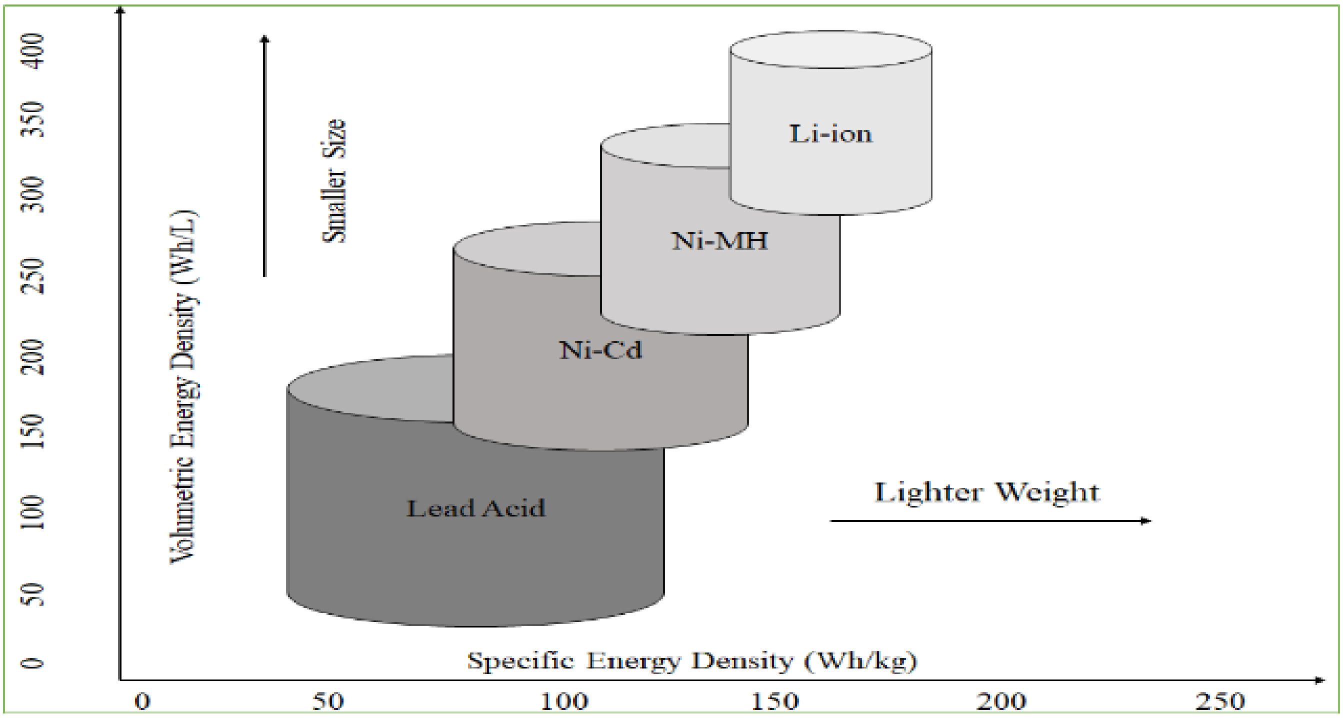

Figure 1- Different types of battery showing Li-ion batteries

MACHINE LEARNING-BASED BATTERY MANAGEMENT SYSTEMS

Machine learning is an application of artificial intelligence. Machine learning enables a wide variety of software applications to predict outputs without being explicitly programmed. Machine learning algorithms build models based on sample data as training data and can make predictions and decisions without being explicitly programmed. AI is central to the development of modern robotics autonomous driving and smart grids. Artificial Intelligence (AI) and its branch of production, known as Machine Learning (ML), is an exciting prospect that will bring about major changes in battery research and development and how to overcome major issues while dealing with large number of data and factors.

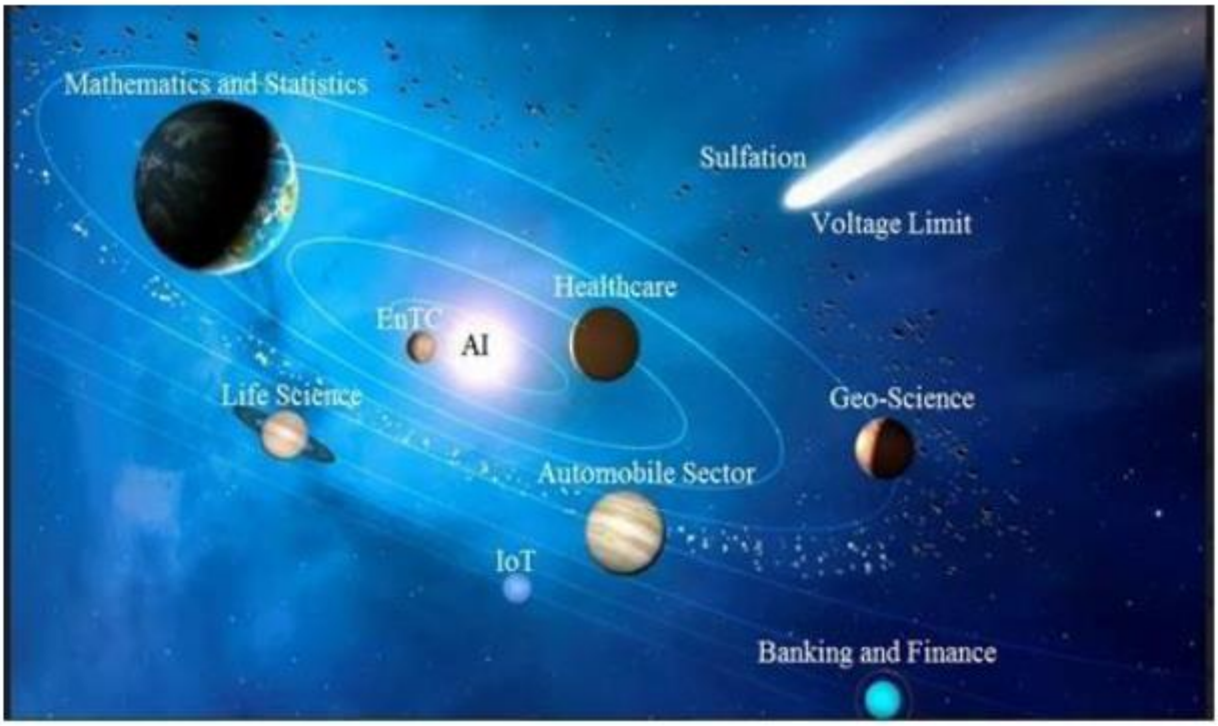

Figure 2- AI and the various areas revolving around them and affecting measuring factors

Machine Learning algorithms are used in many applications, such as computer vision and email filtering, where traditional algorithms fail to do what is expected. Computers learn from the information you give them to perform specific tasks. Machine Learning evolved based on the ability to use computers to explore the structure of data, but we have no theory of what that structure should look like. Machine learning model testing is new data validation error. They often use an iterative approach to learn from data, and that learning can be easily automated. Machine learning (ML) algorithms can extract knowledge from very large and complex data sets without relying on previous underlying relationships between data variables. This study provides insight on the Machine Learning domain and its methodology for analyzing and forecasting battery-affecting factors. However, Machine Learning models are built on Statistical concepts. They are classified into four learning theories: regression, rule extraction, clustering, and classification, each of those including several algorithms. In this article, we are emphasizing Machine Learning paradigms also known as Supervised Predictive Learning Models (SPLM). Starting with very simple regression techniques, we applied more advanced clustering and classification algorithms to validate battery-related issues. In order to predict the potentially non-linear correlations between the most important battery-related elements, various SPLM are being investigated more and more. The benefit of SPLM is that they are more flexible and make fewer, if any, assumptions about the input variables, making them better equipped to interpret outliers, noisy data, or missing data. Battery issues are analyzed using mathematical and/or statistical models and predictions are made after a general understanding of the data.

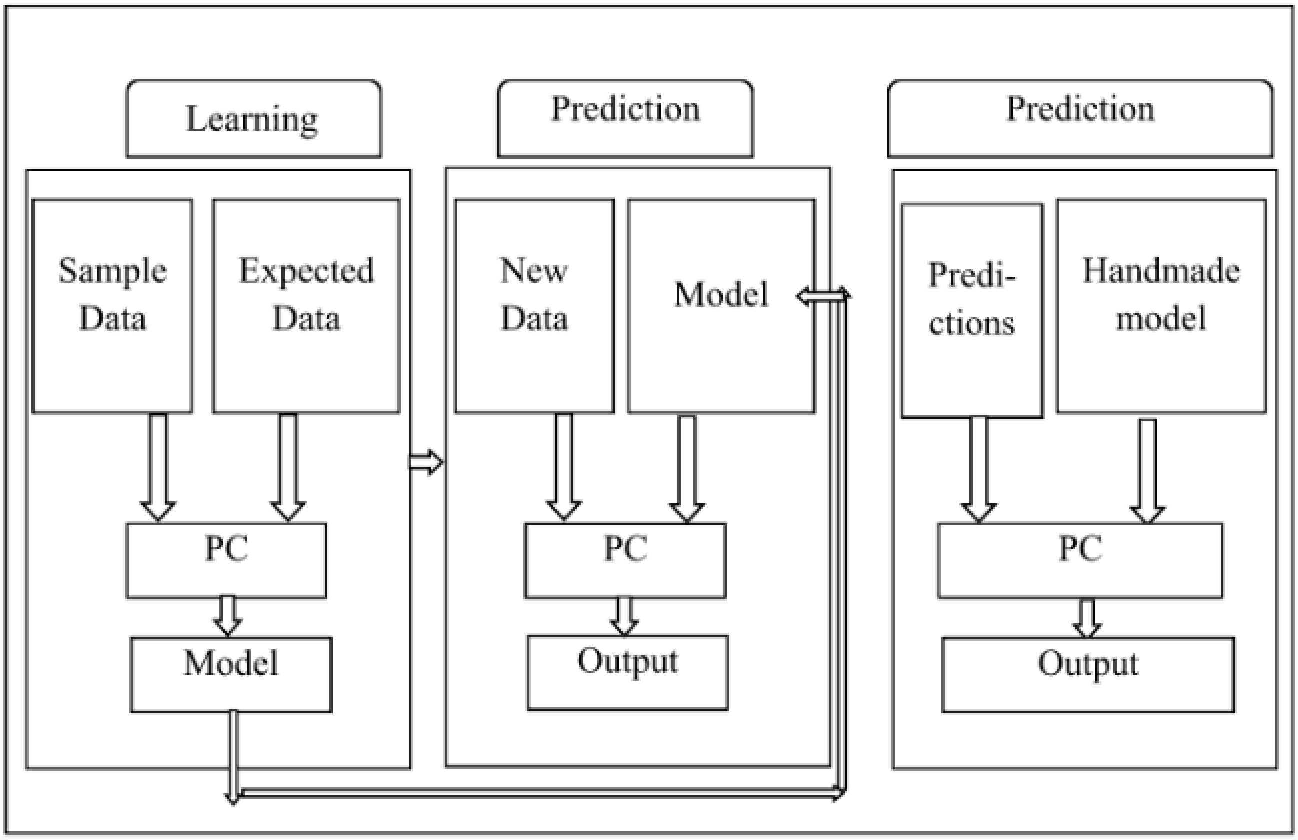

Figure 3- (a) Machine Learning Model Vs. (b) Traditional Mode

BMS USING CLUSTERING

As the charge and discharge times lengthen, Li-ion Batteries become less effective or even fail. The gadget won't operate normally if adequate action is not taken before a battery fails, which could seriously compromise safety. Therefore, these issues may be mitigated by a reliable battery life prediction system. It is challenging for humans to create a solid rule-based algorithm to examine capacity fade since degradation in Li-ion Batteries is not directly reflected in it. Battery management systems are designed based on characterization criteria to check battery health and provide a level of safety to ensure predictable functioning of lithium-ion batteries. Recently, more researchers have started to look at the prospects for the remaining useful life of lithium-ion batteries. Battery behavior is non-linear and cannot be predicted directly, so an indirect approach of estimation and prediction is required. A number of features were observed from the discharge curves of different batteries at different current and temperature levels to estimate her SOH and SOC of the battery. For example, battery B0006 has a current and temperature of 2.0A and 297.15K, while battery B0047 has a current and temperature of 1.0A and 277.15K. Battery arrays mentioned in various studies were taken from other data sources. Some studies used data from battery 40, while others used data up to battery 27 to build the model. These models were created to understand the behavior of battery systems. Others have developed compact models to understand the combined behavior within a system. The machine learning model takes the estimated properties and outputs SOH over all battery discharge cycles in terms of pseudolinear range and arm length. Also, the area under the voltage trace is useful when estimating SOC%. In addition to estimating accurate SOC% for depletion cycles, this method can produce a downward trend for all training cycles. That is, I propose to use the voltage of the battery as a reference point and use a reverse engineer to obtain the SOH. Given a battery at a particular point in time, estimate of SOC is possible. For large datasets, the error obtained is negligible. Despite the fact that polynomial regression models provide the best RMSE compared to other machine learning approaches, this may not be suitable for large datasets. As a result, improved techniques such as ANNs and clustering may prove useful in the future. Finally, ANN is better suited for online SOH estimation because the proposed model requires the entire discharge curve to calculate his SOH and SOC of the battery using a larger dataset.

PREDICTION USING CLUSTERING

Clustering and classification are two pattern recognition techniques used in machine learning. Both techniques have certain similarities, but the difference is that classification uses a defined class to which objects are assigned, whereas clustering identifies similarities between objects. We also propose a clustering composed of different sectors to identify population groups. This review article gains prior knowledge of the types of battery attributes required for battery protection and life extension systems by comparing the variables with those of the cluster. In this study, we use the 'elbow method' to find the optimal number of clusters and characterize each cluster. In this situation, the model generation with value 'k' is identified. After obtaining the number of clusters to create, we propose a k-means algorithm to segment the dataset. After obtaining a good segmentation of the dataset, the next task is to perform the characterization of each cluster. A thorough analysis of each cluster reveals a battery variable, that is. The attributes that classified the H. clusters were sulfation, stress limit, corrosion, passivation, and thermal runaway. Hence, the paper carried out analysis, visualizations, and classification of the incidents using k-means clustering. A detailed study of each cluster discovers composite variables. Clustering is the task of dividing a dataset into groups called clusters. That is, objects are grouped according to these common characteristics and distinguished from other objects called clusters. The purpose of clustering is to split the data so that points in one cluster are very similar and points in different clusters are different. Usually you decide to group under unlabeled data. Using a clustering algorithm means giving the algorithm a large amount of input data and letting it find all the groups in the detectable data, these groups are called clusters. A cluster is a group of data points that are similar to each other due to their relationship to surrounding data points. Clustering is used for things like feature engineering and pattern discovery. Clustering may be an excellent place to start when you are starting with data that you are unfamiliar with. Companies that wish to apply client segmentation, define groupings, and concentrate on certain products or services often need to collect frequent features from their customers. Thus, a firm can defend a specific campaign, service, or product if a sizable portion of its clients have certain characteristics (gender, age, etc.). Clustering is useful for locating comprehensive data and insights in this way. Partitional and hierarchical clustering are the two clustering methods that have received the greatest attention and are utilized the most. These algorithms have been largely used in an extensive range of applications mainly due to their simplicity and ease of implementation relative to other clustering algorithms.

CONCLUSION

Battery behavior is non-linear and cannot be predicted directly, so an indirect approach of estimation and prediction is required. A number of features were observed from the discharge curves of different batteries at different current and temperature levels to estimate her SOH and SOC of the battery. For example, battery B0006 has a current and temperature of 2.0A and 297.15K, while battery B0047 has a current and temperature of 1.0A and 277.15K. Battery arrays mentioned in various studies were taken from other data sources. Some studies used data from battery 40, while others used data up to battery 27 to build the model. These models were created to understand the behavior of battery systems. Others have developed compact models to understand the combined behavior within a system. The machine learning model takes the estimated properties and outputs SOH over all battery discharge cycles in terms of pseudolinear range and arm length. Also, the area under the voltage trace is useful when estimating SOC%. In addition to estimating accurate SOC% for depletion cycles, this method can produce a downward trend for all training cycles.

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