A Comprehensive Review on Optimization and Artificial Intelligence Algorithms for Effective Battery Management in EVs

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***Abstract*—Globally, research on battery technology to be utilized in electric vehicle applications is rapidly expanding to solve the problems of greenhouse emissions and global warming. The efficiency of Electric Vehicles (EVs) are highly depends on the precise measurement of significant factors, as well as on the appropriate operation and analysis of the battery storage system. Unfortunately, inadequate battery storage system monitoring and safety measures can result in serious problems such battery over-charging, over-discharging, overloading, imbalanced cells, heat explosion, and combustion hazards. The quantity of a battery's energy in respect to its capability is described to as the state of charge (SOC). SOC is measured in percentage points and is estimated as the distance between the battery's maximum possible output and its average energy at a specific time under the same issues. State of health (SOH) is the evaluation of a battery's maximum charge amount compared to its starting value when it is first discharged. SOH is calculated using percentage points as its variables. An efficient battery management system, which includes tailored to the content, charging-discharging control, thermal regulation, battery protection and security, is essential for addressing these issues. This paper's objective is to provide a thorough analysis of various intelligent control strategies and battery management system methodologies used in the EV applications. Also, the review assesses the smart algorithms for estimating battery state in terms of their attributes, customization, arrangement, accuracy, benefits, and drawbacks. Finally, prospects and directions for developing a successful sophisticated algorithm and controller are presented in order to create an enhanced battery management system for applications in future, eco-friendly EV technology.**

***Index Terms*—Battery Management System (BMS), Electric vehicle (EV), Machine Learning (ML), Optimization, Renewable Energy Sources (RES), Solar Photovoltaic (PV) systems**

I. INTRODUCTION

In order to support today's life and improve quality of life, the global energy supply is a crucial aspect in the development of technology [1, 2]. The structure of the power grid is dependent on the combustion of fossil fuels. Renewable energy sources are pushed aside in favor of conventional fossil fuels in the energy supply due to the global need for clean energy.

Resources for fossil fuels are few, and rising energy demand contributes to rising pollution. Centralized power generation facilities are inefficient, and these polluting sources that exacerbate environmental problems [3, 4]. Power generation requires structural adjustments in order to switch from the use of conventional energy to that of renewable energy sources in order to address environmental issues. Demand for technology development to expand the use of renewable energy sources [5, 6] in the production of energy is being driven by public interest. Using possibilities to use renewable energy sources and manage sustainability problems in the energy supply is made possible by technological advancement [7].

In recent years, research has been done on the utilization of renewable energy in industrial settings. The invention of innovative methods to meet the rising demand for energy on a worldwide scale has been prompted by pollution and the depletion of fossil fuel resources. Solar and wind energy [8, 9] are two of the renewable energy sources that are rising in popularity. Large public or private corporations have historically taken advantage of these resources due to the requirement for significant investments in high cost infrastructure. Nonetheless, many individual consumers of heat and electricity are now interested in having a significant impact on both the usage and the creation of renewable energies.

These consumers, also known as users, are frequently inspired by a concern for the environment and sustainability [10−12]. This movement depends on electricity being generated in both residential and commercial buildings, typically using PV energy in micro-grids. Hence, installing residential solar energy systems on the roof makes it feasible to generate electricity that is both directly used and, in circumstances of surplus production, exported. The typical architecture model of Battery Management System (BMS) is shown in Fig. 1.

Manuscript received February 27, 2023; revised March 18, 2023; accepted March 29, 2023.
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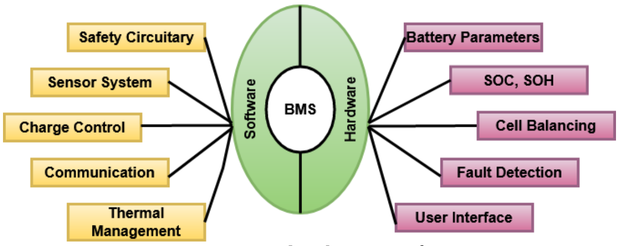

Fig. 1. General architecture of BMS.

Battery technology [13] is integrated into the power system to deliver a steady and continuous supply of electricity. The fusion of solar energy, wind power, and energy storage technologies is being developed through technological advancement. Distributed generating systems using solar and wind energy benefit from a clean, renewable source of power. Yet, the primary issues that must be resolved are the price of energy production, the level of power efficiency, and the consistency of the energy supply. The features of the power system are influenced by the size of the solar and wind power system's unit. Typically, an Electric Vehicle (EV) [13, 14] is one that is propelled by one or more electric motors and is powered by electricity.

It could include a bike or scooter, an electric vehicle, a train, a container or van. In this study, a wide range of studies were conducted on the usefulness of intelligent algorithms for precise battery state estimation, including State of Charge (SOC), State of Health (SOH), Remaining Usable Life (RUL), and SOH. Several controller designs for battery balancing, fault detection, and temperature control were specifically investigated [15−17]. The main problems and difficulties with intelligent controllers and algorithms for BMS were explored. The BMS was given specific future paths for improvement in order to improve precision, versatility, and resilience.

The other portions of this review are categorized into the following units: Section II presents the existing relevant works that correlated to the battery management systems in EV applications. Section III provides a comprehensive analysis on various intelligent algorithms and strategies used for an effective battery management in EV systems. Moreover, the qualitative results of the battery management strategies are analyzed based on various parameters in Section IV. Finally, the overall summary, findings, problems, and impacts of using battery management schemes are presented in Section V with the inclusion of future work.

II. Analysis on Battery Management

The improvement of pedestrian and passenger safety has been a major focus of the automotive industry in recent years owing to several technical developments [18, 19]. On the other hand, the increased traffic on the roadways is to blame for the huge increase in pollution levels in urban areas. EVs are able to reduce environmental pollution, conserve fossil fuels, reduce carbon emissions, and combat global warming, have gained a lot of attention and appeal in order to address these issues. In terms of affordability, reliability, convenience, and profitability, EVs [20, 21] provide an attractive substitute to diesel-powered automobiles. However, widespread EV adoption necessitates the appropriate functioning and prognosis of the battery storage unit, specifically in terms of battery management, charge-discharge control, temperature control, and voltage regulation control. The following are the main roles and responsibilities of an effective BMS [22]:

- Proper temperature management
- Fault identification and rectification
- Voltage, charge and capacity balancing

Reliability and safety are possible with an efficient BMS [23, 24]. Also, it is necessary for data updates, managing battery charge leveling, and recognizing problems that have a significant impact on improving SOC accuracy.

TABLE I: SURVEY ON EXISTING LITERATURE WORKS

Ref./year	Techniques	Description	Pros	Cons
[25] / 2019	Feed Forward Neural Network (FFNN)	This kind of machine learning model is used for fault diagnosis and battery maintenance.	Acceptable accuracy, and easy to implement.	High time to train the data and trapping issues may arise.
[26] / 2020	Support Vector Machine (SVM)	It is specifically used to estimate the SOC of battery used in EV.	Less overfitting, and better prediction accuracy.	System complexity, and increased time consumption.
[27] / 2021	Random Forest (RF)	Mostly used for fault detection and rectification.	Fast in processing, more robust, and highly accurate.	The values of trees may affect the prediction outcomes, and complexity in training.
[28] / 2022	Naïve Bayes (NB)	It can be used for the prediction of battery state.	Less time consumption, and better speed in processing.	It does not capable for handling complex data.
[29] / 2022	Fuzzy Logic (FL)	It is used to predict the SOC of batteries used in EVs.	Effective in computation, and better performance prediction.	Increased memory requirement and high cost consumption.
[30] / 2022	Neuro-Fuzzy Inference system	This type of learning model is used to predict RUL in BMS.	Ensured stability, high accuracy, and ability to handle dynamic errors.	Requires some complex mathematical computations, and lack of robustness.
[31] / 2022	Shannon Entropy mechanism	It is used to identify and diagnose the voltage faults in the EV batteries.	Better prediction outcomes, and ensured reliability.	High processing time, and computational burden.
[33] / 2019	Rule based learning model	It is specifically applied to compute the temperature of battery for proper management.	High accuracy, and reduced error rate.	Inflexibility, and not guaranteed solution.
[34] / 2019	GA	It is widely used in EV applications for battery equalization.	Easy to understand, and minimal time consumption.	Highly sensitive, and low convergence.
[35] / 2020	Particle Swarm Optimization (PSO)	This type of optimization algorithm is used for predicting SOC in EV batteries.	Simpler to execute, highly efficient, and better adaptability.	Requires long time to reach the optimal solution, and convergence is uncertain.

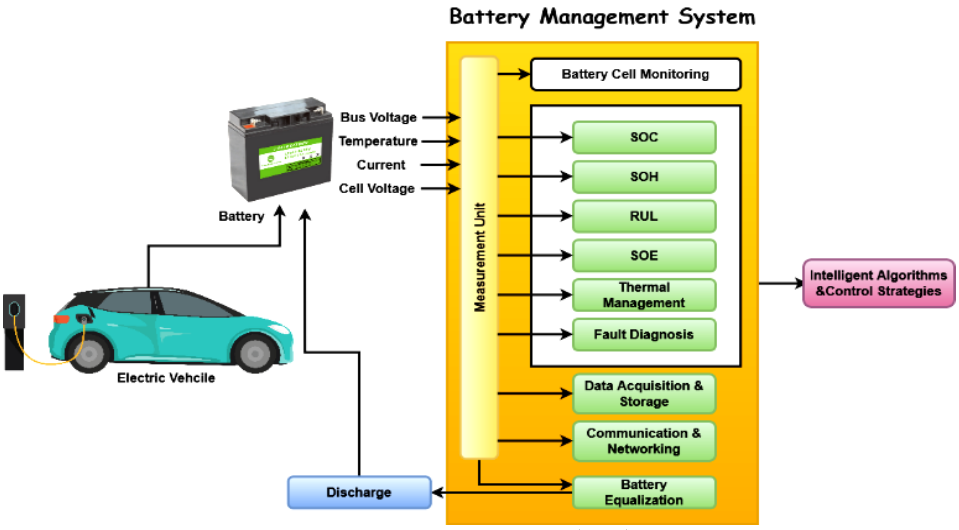

Fig 2. Battery Management System (BMS) in EV.

III. Study on Battery Management System

A new area of study is developing around the creation of the best energy management plans in accordance with the increasing trends in electricity production and utilization. Fig. 2 shows the mode of BMS in EV applications. In the proposed method analyzing the charging and discharging condition using charging circuit.

Electrical vehicle based BMS are to monitoring and control the battery process such as charging and discharging cycle, ensure the healthy condition of the battery. In the proposed method minimizing the risk of battery damaging by ensuring optimized energy is being delivered from the battery to power the vehicle.

In this method BMS of lithium-ion battery will monitor the key parameters like the voltage, availability, temperature during both charging and discharging situations. The controller is the main part of analyzing the input and implementing the output correctly. In electrical vehicle smooth charging performance of entire charging process.

A. Optimization Algorithms Used for Battery Management

Accurate battery status assessment improves battery ageing performance, prolongs battery performance, and ensures secure and dependable EV operation [35, 36]. Prototype and intelligence methods are the two most common categories for battery state estimate methodologies in BMS. To create reliable Rules and mathematical models, the prototype state estimation methodologies need to have in domain expertise like a deeper knowledge of batteries, and a reasonable amount of data [37].

Moreover, in-depth theoretical understanding of physics and chemistry is required for the study of anode, cathode material properties, electrolytic process, amplitude and phase. The experimental testing must also be carried out with a lot of time, comprehensive research, and technical knowledge. If the parameters of the battery model are appropriately evaluated, the model-based SOC estimate approaches have a shorter offline cycle time and yield consistent results.

The amount of charge that can be used to power a vehicle is known as SOC [38, 39]. The accurate assessment of SOC is crucial for improving charging and discharging strategies and expanding battery durability. The topic of SOC estimation for lithium-ion batteries has been covered in a variety of articles. The optimization techniques, regression analysis, and time series algorithms are the most commonly used intelligent mechanisms for estimating the SOC [40].

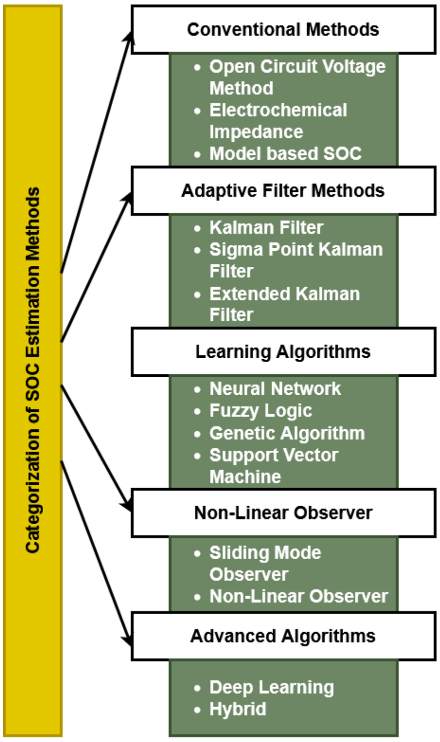

Fig. 3. Methods used for SOC estimation.

Heuristic optimization methods have made significant advancements in SOC accuracy recently due to the merging of cognitive algorithms and heuristic methods. Hyper parameter optimization can lead to the establishment of a composite adaptive optimization algorithm for SOC estimation, which ultimately increases SOC estimation [41] accuracy under various operating conditions. In order to develop underlying heuristics to tackle particular optimization problems, designers might employ meta-heuristic algorithms as upper level general approaches. Typically, optimization is the process of determining the best values for the variables in a specific problem in possible to lessen or optimize an objective function. Numerous academic disciplines face optimization issues. Several measures must be followed in the effort to resolve an optimization problem. It is first important to determine the problem's parameters. Problems can be categorized as either continuous or discrete depending on the characteristics of the parameters. Second, it's important to recognize the constraints that are imposed on the parameters.

Fig. 3 depicts the different types of methods used for estimating battery SOC. Furthermore, it is important to look into and take into account the provided problem's objectives. Here, single-objective and multi-objective optimization issues are differentiated [42]. Consequently, a suitable optimizer should be selected and used to solve the problem based on the types of variables, restrictions, and number of targets identified. To discover the best solution, mathematical optimization mostly uses gradient-based creation of the relevant functions. These methods have some drawbacks despite the fact that numerous researchers continue to employ them. Local optima trapping is a problem for statistical optimization techniques [43, 44].

This occurs when an algorithm fails to reach the global optimum because it thinks a local solution is the global solution. For the purpose of avoiding local optima, probabilistic approaches rely on random variables. Each one begins the optimization process by popping up with a single or a collection of arbitrary solutions to the given topic [45]. Compared to mathematical optimization techniques, they only need to evaluate the solutions using the objective function rather than having to figure out a solution's gradients. Based on the computed objective values, decisions are made about how to improve the solutions.

The most widely used stochastic optimization techniques use population-based algorithms that are inspired by nature. Those techniques resemble how living things typically solve challenges in nature. For all living things, survival comes first. They have been changing and adapting in many ways to reach this goal. As the best and greatest optimizer on the planet, nature is a good place to look for inspiration [46]. In the former class, only one randomly selected solution is created and enhanced for a certain issue. Here, some of the most frequently used popular optimization algorithms are discussed for battery management.

1) Grasshopper Optimization

A recent swarm intelligence system called the Grasshopper Optimization Algorithm (GOA) [47] was inspired by the hunting and aggregating activities of grasshoppers in the ecosystem. Several optimization issues have been successfully solved using the GOA method in a number of different fields. High exploration has been shown to be advantageous for the GOA, which also exhibits a very quick convergence time. This algorithm's unique adaptive mechanism equalizes exploration and exploitation. Due to these features, the GOA algorithm may outperform competing methods and be able to handle the challenges of a multi-objective search space. When solving issues with several objectives, a multi-objective algorithm looks for two outcomes. One is that it should be possible to find very precise approximations of the real Pareto optimal solutions. Another is that the solutions ought to be evenly divided among all the targets. As decision-making occurs after the optimization process, it is crucial in a posteriori approaches.

2) Cuckoo Search Optimization

Cuckoos are remarkable birds not only for the lovely sounds they can produce but also for the aggressive way in which they reproduce. Certain species, like the any part of the area cuckoos, lay their eggs in Social nests, but they may also take eggs from other nests to enhance the likelihood that their own eggs will survive. The following assumptions are made in this optimization [48]:

- Each cuckoo only produces one egg at a time, which is then dropped into a random nest.
- The best nests with top-notch eggs (solutions) will be passed down to the following generations.
- A host has a finite amount of host nests available to them, and they have a chance [0, 1] of finding an alien egg.
- In this situation, the host bird has two options: either toss the egg out or leave the nest and start a brand-new nest somewhere else.

3) Krill Herd Optimization

A recent swarm-based meta-heuristic optimization method called Krill Herd (KH) [49] is motivated by the krill behavioral biases. The KH optimization process's objective function is dependent on the krill's position's proximity to its food source. On numerous benchmarks and engineering applications, it has been demonstrated that the KH technique performs better than a number of cutting-edge meta-heuristic algorithms. According to KH [50], the separation between the location of the food and the krills' positions is an objective measure. The three steps below can be used to divide the KH optimization process:

1. Motion caused by other krill
2. Hunting activity
3. Stochastic diffusion

4) Fruit Fly Optimization

A novel technique for locating global optimum called FFO (Fruit fly optimizations) based on how fruit flies find food [51]. The fruit fly has clear perspective and osphresis than other species. The fruit fly has a two-step process for gathering food: first, it uses its osphresis organ to sense the food source and then flies in that path; second, when it gets near to the food destination, it can utilize its empathetic sight to locate the food. Setup, osphresis foraging, population estimation, and perception are the four stages of this method.

5) Other Optimization Algorithms

Due to their resilience and the clarity of the results they provide, the Harmony Search Algorithm (HSA) [52], have gained an image for being superior to other search methods in addressing optimization challenges. A swarm intelligence method called Whale Optimization (WO) [53] has been presented for persistent optimization issues. It has been demonstrated that this algorithm performs as well as or better than some of the current computational methods. WOA has drawn inspiration from the humpback whales' hunting techniques. Every solution in WOA is considered to be a whale. A whale attempts to fill in a new location in the search area that is referenced as the best member of the group in this solution. The whales employ two different techniques to both attack and locate their prey.

Then, the prey are enclosed during the initial procedure, and bubble nets are made in the subsequent. In terms of optimization, whales search for prey by exploring their environment, and they exploit their environment during an attempt. For tackling both continuous and discrete problems, the original Cat Swarm Optimization (CSO) algorithm was developed [54]. Cats are naturally lazy creatures who spent the majority of their existence sleeping. But, although they are sleeping, cats have heightened awareness of their surroundings and are conscious of what's going on.

They are constantly alertly examining their surroundings, and whenever they spot a target, they begin to move fast in that direction. The Butterfly Optimization Algorithm (BOA) is a new meta-heuristic algorithm that draws from the natural world and is based on how butterflies search for food. To carry out optimization, Butterflies act as candidate solutions for BOA. Butterfly sense receptors are used to locate the source of food in a biological sense. According to BOA [55], a butterfly will produce fragrance with an intensity that is connected to its fitness, meaning that as it goes from one place to the other, its fitness will change as well.

The fragrance will travel across distance and other butterflies will be able to detect it, which is how the butterflies can exchange private information and create a network of shared Social knowledge. The Moth Flame Optimization (MFO) begins by creating moths at random in the solution space, determining each moth's fitness values, and then labelling the ideal position with a flame. The next step is to update the moths' positions using a spiral movement function to acquire optimal locations that are labelled by a flame, update the new greatest individual stances, and then replicate the pre requisites until met the termination criteria.

B. Machine Learning (ML) Algorithms used for Battery Management

SOH is the difference between the charge capacity of an old battery cell and the charge capacity of a brand-new battery cell needed to meet operating requirements. SOH is essential for determining the battery's present state of health. The literature has published a number of approaches to forecast SOH of lithium-ion batteries. Fig. 4 shows the ML based battery state estimation model.

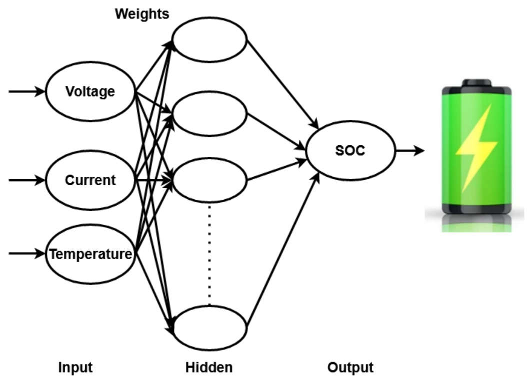

Fig. 4. Battery state estimation using ML model

Mostly, the machine learning and deep learning based algorithms [56] are increasingly used for the prediction of battery SOH. The secure, dependable, and efficient operation of EVs depends heavily on safe usage of batteries. As a result, it is crucial to build an effective diagnostics and fault handling mechanism because even a small malfunction could lead to serious issues with the health of the battery. BMS fault mechanisms can be divided into three groups: sensory fault, controller fault, and battery fault. These fault mechanisms are typically quite complex. The defects in the power, current, and sensing devices are referred to as sensor faults in BMS. The prediction accuracy of SOC, SOE, SOH, and RUL can vary due to flaws in the current sensors. Also, the battery must be operated within the manufacturer-recommended safe voltage range and humidity [57]. The battery's performance may suffer or possibly cause problems if the calculated results surpass the limit. Besides that, temperature and current sensor errors could induce battery harmonization errors in BMS. The fault diagnosis model of BMS in EV is shown in Fig 5.

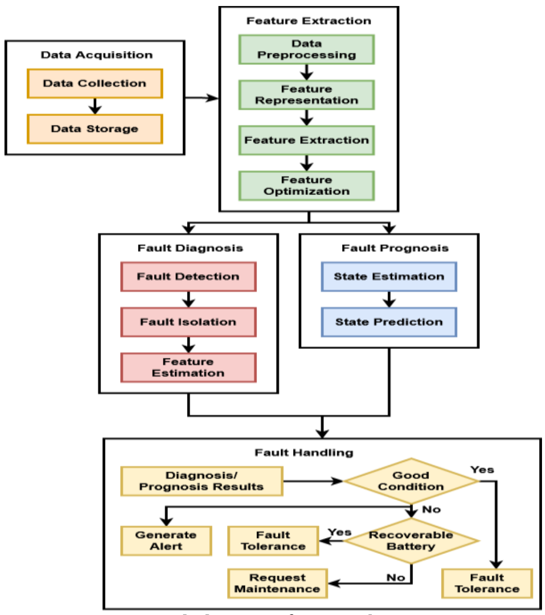

Fig. 5. Fault diagnosis framework in BMS.

IV. DISCUSSIONS

Because of the complex nature of the algorithms used, as well as other internal and external considerations, the deployment of intelligent techniques used in BMS for EV applications has become a significant challenge. Three categories—algorithm-related issues, deployment issues, and battery-related concerns—distinguish the major problems and difficulties. Intelligent approaches have some drawbacks, although having shown promising solutions for the development of a successful BMS [58]. Although ML-based methods can produce acceptable results, their performance is limited by processing time and memory size. Although the logistic and probabilistic approaches are resistant to problems with distortion, ambiguity, and information generalization, they are unable to produce precise solutions in imbalanced datasets and quasi systems [59]. Deep learning algorithms have produced remarkable results in SOC, SOH, and RUL prediction; nevertheless, they require high-quality, a bunch of data, along with fast and expensive computing processors.

The accuracy of the optimization strategies may vary because of the local optimal pit, inadequate searching capability, and erroneous input variables, however they can be integrated with machine learning and deep learning algorithms. The intricacy and variability in the observed data can be measured using the entropy approach, although it has the drawback of requiring a lot of processing. It is difficult and demanding to integrate optimization into intelligent procedures and control schemes. Intelligent strategies could be used with a variety of optimization techniques. Yet, in terms of processing time and fast convergence, optimization performance differs from method to method [60].

Also, there are numerous operational stages and factors used in the framework of optimization algorithms. Extensive understanding and subjective condition are required for parameter initialization and operational loop execution in optimization. Although though the incorporation of optimizations into learning algorithms in BMS has shown to provide significant benefits in terms of precision, resilience, and accurate prediction, they do have certain drawbacks related to computational burden and long learning times. If the convergence, functionalities, and dimension specifications are not adequately addressed, the integration of optimization may produce disappointing results. To get satisfactory results in predictions and controlling operation in BMS, it is crucial to use the appropriate optimization approach.

V. Conclusion

Due to high peak power and hard charging/discharging cycles during both acceleration and deceleration phases, especially in urban driving circumstances, EV batteries tends to degrade more quickly. Due to the availability of big data, powerful processing power, and large data storage capacities, several analyses and evolutions of intelligent algorithms and control techniques for BMS in EVs have been carried out recently. This article examines the present development of intelligent algorithms towards battery status prediction to make a preliminary effort. The analysis has shown that the intelligent algorithms have demonstrated higher results when it comes to precision, scalability, robustness, and effectiveness in battery status estimation.

This assessment also covers several control methods for temperature regulation, fault diagnosis and prediction, and battery charge balancing, focusing attention on the type, goals, results, advantages, and drawbacks of each method as well as the limitations of the research. The solution to these problems is an effective battery management system that includes content-specific charging-discharging control, thermal regulation, battery protection, and security. The purpose of this research is to present a comprehensive examination of several intelligent control strategies and battery management system methodologies used in EV applications. The evaluation evaluates smart algorithms for predicting battery state in terms of their characteristics, adaptability, organization, accuracy, advantages, and disadvantages. In order to produce a successful advanced algorithm and controller for use in the development of future, environmentally friendly EV technology, possibilities and directions for their development are finally offered.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

D. Manoj carried out the survey as part of her postgraduate studies. F. T. Josh has provided advice on method structure, and all review issues have been handled. The final version was accepted by the author.

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