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AI TECHNIQUES IN ELECTRIC VEHICLE BMS.

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ABSTRACT

Electric vehicles (EVs) have gained significant attention in the automotive industry as a sustainable solution to reduce carbon emissions and address global environmental concerns. However, the efficiency of EVs can decline over time due to the degradation of battery health and performance. In this context, artificial intelligence (AI) techniques have emerged as promising tools to enhance EV safety, reliability, and efficiency by enabling accurate battery health assessment, fault detection, and thermal management. This research explores the impact of AI-based approaches on Battery Management Systems (BMS) in electric vehicles and evaluates their effectiveness. A comprehensive statistical analysis of relevant BMS-related literature is conducted using multiple evaluation methods. Key aspects such as research trends, authorship patterns, collaboration networks, publication sources, keyword distribution, and research categorization are analyzed in detail. Furthermore, the study examines the objectives, contributions, advantages, and limitations of various advanced AI techniques applied in BMS. It also highlights critical challenges and open issues in the field, along with practical recommendations and future research directions. The findings of this analysis provide valuable insights and serve as a guiding framework for researchers aiming to develop innovative, efficient, and sustainable battery management technologies for electric vehicles.

Keywords: artificial intelligence (AI), battery management system (BMS), electric vehicles, machine learning, state of charge, state of health.

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1. INTRODUCTION

With the rapid advancement of technology, the fields of machine learning (ML) and artificial intelligence (AI) have been booming in recent years. In several practical contexts, it started to show signs of usefulness and improvement over more traditional approaches. To ensure passenger safety, the car industry has invested much in developing effective and dependable systems [1]. But as the number of cars on the road increases, so does the air pollution level in cities [2]. According to EU statistics [3], the transportation industry is responsible for around 27% of all greenhouse gas emissions, with the majority of these emissions coming from vehicles. When it comes to ease of use, precision, and dependability, electric vehicles (EVs) have surpassed their fossil fuel-powered predecessors [4]. On the other hand, there are a number of drawbacks to electric vehicles [5]. These include a short range, a lengthy charging time, and decreasing battery efficiency under different conditions. We need a smarter and better battery management system (BMS) to fix the major issues such as thermal runaway, cell unbalancing, overcharging, over-discharging, overheating, and fire dangers [6].An intelligent and efficient battery management system (BMS) is required to perform tasks such as temperature control, charge balancing, fault diagnostics, and estimating remaining usable life (RUL), state of charge (SOC), state of health (SOH), and status of energy (SOE) [7]. You may use techniques like open circuit voltage, Fuzzy Logic, Artificial Neural Networks, Kalman filters, and the Coulomb counting approach to estimate SOC. One of the most reliable ways to measure capacity using state-of-charge (SOC) data is to measure the difference in amp-hours (Ah) between two specific locations.Incorporating recursive algorithms like advanced Kalman filter (KF) methods or recursive least squares into the resistance estimation utilizing SOH approaches makes it more adaptive compared to only averaging delta voltage divided by delta current [8]. The BMS is an essential component of an EV since it regulates the charging and discharging of the battery, keeps the electrical parameters within safe ranges, and prevents the battery from being overcharged or over discharged. Parameter computation in BMS has traditionally relied on electrochemical models. Issues with accuracy, robustness, safety, and battery performance/lifespan are common outcomes of using these models. Adaptability to various driving conditions and user behaviors, high-quality sensors, accurate data, and advanced modeling techniques are all crucial components of well-designed BMS algorithms that must be developed and implemented to overcome these challenges.

With the rise of AI and ML, the emphasis has shifted from data-driven algorithms to more conventional ones. Thanks to AI and ML, parameter estimation is now much more accurate, and they're also more flexible to deal with changes in the environment. Artificial intelligence methods have the potential to greatly improve the efficiency and usefulness of EV BMS [9]. There are many advantages to using an AI-driven BMS in electric cars (EVs), such as better performance, safety, energy efficiency, and overall user experience. It helps the battery last longer as well. Machine learning (ML) offers a practical solution to the problem of system complexity and unpredictability because of its inherent data-learning capabilities and low dependence on mathematical representations of physical systems. More and more, data- driven machine learning models are being used for battery state prediction as a result of recent developments in machine learning applications [10]. Deep learning (DL), support vector machines (SVM), and neural networks (NN) are common ML-based mapping models [11].Here is how the remaining portion of the paper is structured: Part II provides a methodology overview for machine learning, Part III is devoted to deep learning, Part IV is all about optimization algorithms, and Part V is all about rule-based techniques. Section VI delves into potential avenues for further research, while Section VII delves into the findings.

2. MACHINE LEARNING APPROACHES

2.1 Back Propagation Neural Networks (BNN)

Supervised learning is used to train members of a specific kind of ANN, known as a Back Propagation Neural Network. This idea is the cornerstone of ML and deep learning. Through training-time adjustments to weights and biases, back propagation tries to reduce the discrepancy between a neural network's predicted and actual outputs for a given batch of training samples. Changing these weights repeatedly allows the network to decrease error, which is defined as the discrepancy between predicted and actual outputs.

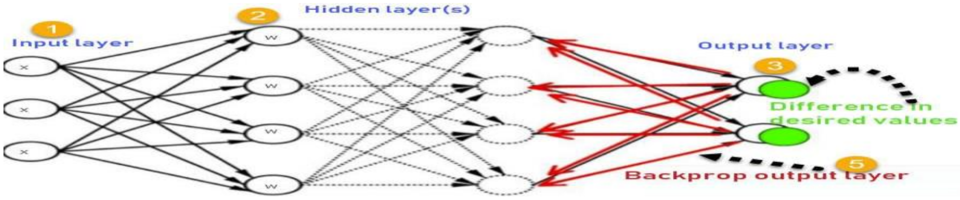


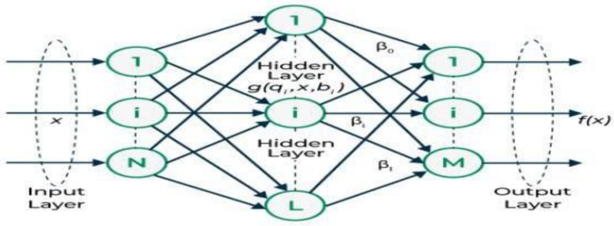
Figure-1. Back Propagation in Neural Network: Machine Learning Algorithm.

One popular method for SOC estimation in BMS applications is the BPNN methodology, which consists of an input layer, a hidden layer, and an output layer structure.A proper activation function and training technique are used to perform it. The block diagram og Back Propagation in Neural Network is shown on Figure-1. For instance, a model for calculating the SOH and RUL of lithium-ion BMS was created by Ma and colleagues. In order to improve the results and find the best settings, particle swarm optimization (PSO) was mixed with BPNN. The results showed that the total error was 1.01% and the root mean squared error was 0.78%, as shown in [13]. Because of their skill in modeling complicated relationships within battery data, BPNNs are a useful tool for state-of-charge estimation. In addition to handling non- linear patterns, BPNNs are able to adapt to changing battery conditions.It is critical to optimize models, take data preparation seriously, and carefully evaluate computer resources in order to use BPNN advantages in battery management efficiently. Lead acid (LA) and lithium iron phosphate (LFP) batteries' SOCs were determined by Vidal *et al.* [14] using the BPNN technique.Five rounds of light vehicle testing were used to evaluate the suggested model. The computations showed that the RMSE for the LA battery was 0.84% and for the LFP battery it was 0.33%. The BPNN model was used by Driscoll *et al.* [15] to project SOH using the NASA Ames PCoE Battery data set. A feature-based SOH model was constructed using the charging process's temperature, voltage, and current characteristics. The SOH forecasts were quite accurate across a range of situations, with coefficients of determination ranging from 0.896 to 0.992.

2.2 Extreme Learning Machines (ELM)

An ELM-based machine learning technique is used for supervised learning problems in the neural network area. They are an alternative to the more conventional gradient-based learning techniques that were introduced to neural networks as a training option. Reducing the computational burden of training neural networks, particularly in terms of training time, is the primary goal of ELM.While conventional neural networks like BPNN and FNN train the hidden-to-output and input- to-hidden connections separately, ELM takes a different tack. An outline of Extreme Learning Machines (ELM) is shown in Figure-2.

Figure-2. Extreme Learning Machines (ELM).



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Using the ELM technique, Pan *et al*. [16] proposed a model for estimating SOH. This model has shown exceptional precision and quickness. The results show that an estimated error of less than 2.5% is possible. When dealing with very complicated hierarchical data structures, ELM may not be as flexible as other DL algorithms, while being faster and easier to utilize during training.A cloud-based BMS with a unique training method and data preparation approach was created by Li *et al*. [17] using the ELM algorithm. The suggested model produced respectable outcomes, with a 2% SOC error and a 3% terminal voltage error, respectively. Using an ELM controller, Jinag *et al*. created a novel hybrid system for energy storage [18].According to the reports, the ELM controller reduced battery life loss by 6.51% and increased power use by 3.78% compared to the rule-based controller.

2.3 Random Forest (RF)

When it comes to machine learning, Random Forest is a go-to for both classification and regression jobs because of how versatile it is. In the training phase, it creates a large number of decision trees and then takes the average prediction (for regression) or mode (for classification) from each tree. The steps of the Machine Learning Random Forest Algorithm are indicated in Figure-3.

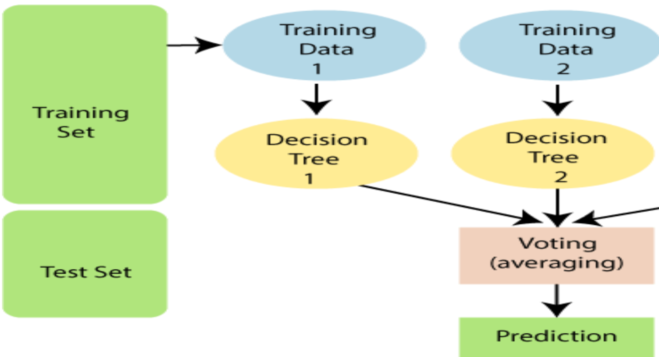

Figure-3. Machine Learning Random Forest Algorithm.

Careful evaluation of computational resources and post-model interpretation methods may be necessary to fully use RF's benefits in battery management. The RF model was used by Wang *et al*. [19] to forecast the SOH and RUL of a lithium-ion battery. According to the authors, the estimated SOH had a mean error of 1.8152%, which is less than that of other traditional models.In order to determine SOC, the authors of [20] used a variety of lithium-ion battery materials and the RF approach. Tests performed at ambient temperature and with varying EV driving cycles confirmed the product's viability. Figure-4 indicates the Machine Learning Random Forest Algorithm. In the DST drive cycle, RF achieved an RMSE of 0.382% and an MAE of 0.193% in the HPPC test conducted at 25 ◦C, demonstrating good performance.

2.4 Radial Basis Function Neural Network (RBFNN)

For radial basis function neural networks (RBFNNs), the activation functions are radial basis functions. In this three-layer network, radial basis function neurons are located in the hidden layer, which is separate from the input and output layers. Among RBFNN's many uses are clustering, pattern recognition, and function approximation. The main components of a radial basis function neural network (RBFNN) are an input layer, an output layer, and a hidden layer composed of RBF neurons. The output of each neuron in an RBFNN's hidden layer is determined by a radial basis function that is specific to that neuron and is dependent on the distance between the input data and its center point. The use of RBFNN for benefit estimate in battery SOC has been shown Figure-4.

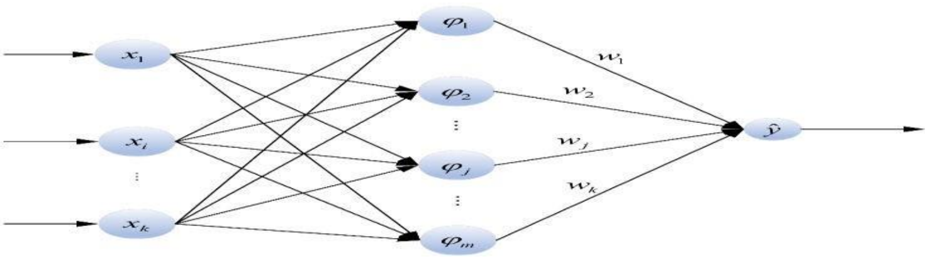

Figure-4. Radial basis function neural network.

Based on RBFNN, Wu *et al*. [21] suggested a better way to estimate the SOH of lithium-ion batteries. The findings showed that this technique can accurately estimate the SOH, with an error margin of no more than ±4%. The SOH of lithium-ion batteries may be predicted using a hybrid model that Zhang *et al*. [22] developed by integrating RBFNN and PSO. Based on the testing findings, the hybrid model reduced the root mean square error (RMSE) by 0.23% and the average absolute error (AAE) by 0.34%. Thanks to its superior capability to estimate complicated functions utilizing radial basis functions, RBFNN excels in complex and nonlinear battery applications.

2.5 Gaussian Process Regression (GPR)

With its data-driven and probabilistic approach to forecasting battery behavior and improving efficiency, GPR has shown its worth in the BMS arena. Electric vehicles (EVs) and renewable energy storage are two industries that employ GPR because accurate predictions of battery deterioration and remaining life are critical for successful and profitable operations. GPR provides a versatile and strong method for managing batteries, allowing for accurate tracking and adjustment of battery performance, considering the uncertainties present in real- life situations. A GPR-based model for end-of-life (EOL) prediction was presented by Meng *et al*. [23]. According to the authors, compared to the other popular models, the GPR basis technique's mean EOL cycle forecast is more accurate and has a smaller prediction uncertainty range. To estimate the SOC of a lithium-ion battery, Deng *et al*. [24] presented a GPR model. Probabilistic predictions, nonparametric modeling, and accurate approximation of nonlinearity were highlighted as three key advantages of the GPR technique by the authors. Although the estimation error varied with temperature, aging circumstances, and dynamic cycles, the testing findings showed that it always stayed below 3.9%.

2.6 Support Vector Machine (SVM)

Using support vector machines (SVMs) for classification and regression tasks is an example of supervised learning. Its principal use is in classification issues, where the objective is to choose the best decision boundary for classifying data points. Support Vector Machines (SVMs) are useful in Big Data Management Systems (BMS) because of their efficiency with high-dimensional data, robustness to noise and outliers, high accuracy in classification and regression tasks, and their versatility. Support vector regression (SVR) and principal component analysis were used by Jiang *et al*. [25] to predict the fading of capacity in lithium-ion batteries. With an R2 value of 0.9194, the data showed that SVR is more accurate than GPR. An online-based approach for calculating SOH with a partial charge segment was developed by Feng *et al*. [26]. Using two commercially available Li-ion batteries for training, validation, and testing, the SOH was found to be less than 2% off, according to reports. By combining cycle data, voltage and temperature profiles, and various operating settings with a unique multistage support vector machine (SVM) approach, Patil *et al*. [27] were able to predict the RUL of lithium-ion batteries.Faster computations appropriate for real-time RUL estimations were shown by the findings.

2.7 Reinforcement Learning (RL)

Reinforcement learning (RL) agents interact with their environment to learn how to make sequential choices that maximize cumulative rewards or fulfill goals. It follows the people and animals' learning process of making mistakes and learning from their actions in various settings. Heba *et al*. examined a reinforcement learning- based EV charging management system [28]. Compared to standard BPNN and RBFNN approaches, which need a lot of training data and are dubious about real-time viability, reinforcement learning (RL) offers lower energy consumption and longer battery life.

Gabalawy [29] optimized EV virtual power plants using RL. The results indicated that RL improves robustness, convergence, and smart grid VPP optimization. RL increased balancing power 48% to 82% and cut fleet charging expenses 25%. To estimate lithium- ion battery state of charge (SOC), Minho *et al*. [30] used reinforcement learning (RL).A lot of data improves RL training accuracy for SOC estimation, the scientists discovered. Simulation data on battery charging and discharging confirmed the concept. RL optimizes EV charging and discharging, adapts to changing driving circumstances, and boosts energy efficiency. RL in EV BMS may improve energy management for range, adapt to different driving styles,and optimize battery utilization in real time.

Table-1. Review of ML techniques for advanced BMS applications.

ML Method	Target	Key Findings	Advantages	Disadvantages
BNN	RUL and SOH	RMSE is 0.78% AAE is 1.01%	• Adaptability. • Nonlinear Modeling. • Automatically feature Modeling.	• Lack of interpretability. • Lengthy training time.
ELM	SOH	The greatest estimation error is less than 2.5%	• Scalability. • Simple implementation.	• Not easily interpreted. • Over-fitting in data with noise.

RF	SOH and RUL	The average error of the estimated SOH is 1.8152%.	• Greater Accuracy • Sturdiness against erratic data.	• Inability to be interpreted. • Potential for over-fitting.
RBFNN	SOH	With this hybrid approach, the average absolute error and root mean square error may be reduced by 0.23% and 0.34%, respectively.	• Local learning and generalization. • Interpretability. • Nonlinearity and Function.	• Inadequate sequential learning. • Limited scalability.
GPR	SOC	The estimation error of this model is less than 3.9%.	• Flexible Modeling • Able to foresee uncertainty • Interpretability.	• Limited Scalability. • Computational complexity. •
SVM	SOC	The maximum relative error is less than 3%, and the Average relative error is less than 2.5%.	• Flexibility for Non-Linear data. • High Accuracy.	• Model complexity. • Difficulties with a large data set.
RL	SOC	The estimation error is dependent on how well RL is trained using a significant amount of data.	• Algorithm Generalization • Self-governing learning. • Adaptability and flexibility.	• Interpretability concerns • The significant amount of data required

3. DEEP LEARNING APPROACHES

3.1 Long Short-Term Memory (LSTM)

Traditional RNNs often suffer from disappearing and bursting gradients; LSTM was designed to fix this. If you need to analyze and generate predictions from sequential data, such as time series, audio, or natural language, LSTMs are a great choice. Improved accuracy in battery health forecasts, efficiency in battery resource management, and the capacity to discern long-term relationships necessary for battery behavior forecasting are all outcomes of using LSTMs in BMS for EVs. Long short-term memories (LSTMs) are able to handle sequential input, mitigate the disappearing or exploding gradient problems encountered by conventional recurrent neural networks, and keep memories for long periods of time. Long short-term memories (LSTMs) are also flexible enough to learn from sequences of varying durations. However, using LSTMs in BMS for EVs comes with several drawbacks, such as how complicated they are, which may make them difficult to comprehend learnt representations, and how much data is needed for successful training. Basnet and Ali looked at 5G network security concerns for LSTM-based electric vehicle charging stations [34].When it came to detecting cyberattacks in the monitoring system, our model virtually hit 100% accuracy. En and Du [35] compared LTSM, SVM, and GPR to forecast the SOH of lithium-ion batteries. Several performance indicators, including datasets,input characteristics, hyperparameter modifications, advantages, and disadvantages, were used in the study. One way to estimate SOC using LSTM was suggested by Ren *et al.* [36]. Using the PSO technique, the LSTM hyperparameters were fine-tuned. Testing the adaptability of the proposed PSO-based LSTM was done using EV driving cycles and random noise. A good level of SOC error of 0.5% was shown by the results.

3.2 Convolutional Neural Network (CNN)

Within the realm of deep neural networks, Convolutional Neural Networks (CNNs or ConvNets) mainly function to process and evaluate grid-like ordered input, particularly media files like photos and videos. Their expertise is in solving computer vision problems; however, they have found use in domains like voice recognition and natural language processing as well.Computer vision applications, such as picture identification and analysis, make substantial use of convolutional neural networks (CNNs), a kind of deep learning model.Convolutional neural networks (CNNs) provide prospective uses in BMS, despite their infrequent association with the latter. When it comes to electric car battery temperature management and the establishment of SOC and SOH, this is especially true. To calculate EV batteries' SOC, Mazzi *et al.* [37] used the CNN model. The outcomes were evaluated in relation to GRU. With a root- mean-squared error (RMSE) of 2.33% and an MAE of

1.62%, the 1D CNN model proved to be more accurate than the GRU-based one.

3.3 Gated Recurrent Units (GRU)

One kind of RNN architecture that can identify and express relationships in sequential data is GRU, which is similar to LSTM networks. In the domain of long-range dependency modeling, GRUs provide equivalent performance to LSTMs while being more computationally cheap. With GRUs in BMS for EVs, we can better estimate the state of the battery, manage battery resources more efficiently, and capture long-range dependencies that are critical for forecasting how the battery will behave. GRUs have shorter training periods than LSTMs since they are simpler and use fewer parameters. Their capacity to efficiently handle sequential data is a significant advantage they provide.While avoiding vanishing gradient concerns and using fewer computing resources, GRUs still manage to give competitive performance.Problems for BMS in EVs could arise from the fact that GRUs, being abstract, might not be able to grasp long-term relationships to the same extent as LSTMs. Interpretation issues with the obtained representations are another potential stumbling block. Activation function layer-based GRU networks, as suggested by Duan *et al*. [38], outperformed LSTM and conventional GRU models in terms of SOC prediction accuracy and consistency.In the presence of measurement data noise, the experimental findings showed that the GRU-ATL model outperformed the regular GRU model and the LSTM model in terms of SOC prediction accuracy, with a margin of 0.1-0.4% and 0.3-0.7%, respectively. The RMSE and MAE of the SOC remained consistent, falling within the ranges of 0.7% and 1.9%, respectively, according to the GRU-ATL model. To uncover the hidden relationship between SOH and input data, Zhang *et al*. [39] presented a GRU-based SOH model that uses a sparrow search approach to boost the learning rate of the model. A single battery and a battery pack were both used in the appropriate experimental trials to evaluate the practicality and usefulness of the suggested solution.

Table-2. Review of deep learning techniques for advanced BMS applications.

DL Method	Target	Key Findings	Advantages	Disadvantages
LSTM	SOC	Estimation error 0.5%.	• Excellent Accuracy. • Capable of managing irregular samples.	• Difficulty managing imbalanced data. • Long data training time was necessary.
CNN	SOC	RMSE 2.33% MAE 1.62%	• Superior results compared to GRU with large data features.	• Requirements for data. • Computational resources. • Processing in real time.
GRU	SOC	The mean absolute error is between 0.7 and RMSE in between 1.2-1.9%.	• Simplicity in execution. • Perfect for brief to moderate sequences.	• Extremely sensitive parameters. • Limited application for intricate sequences

4. OPTIMIZATION ALGORITHMS

4.1 Genetic Algorithm (GA)

The principles of genetics and natural selection inform genetic algorithms (GAs), which are search and optimization tools. Their use in estimating optimization and search issue solutions stems from their ability to mimic the processes of natural selection, mutation, crossover, and survival of the fittest. A model that determines the state of charge of lithium-ion batteries via GA optimization [40] was proposed by Ma et al. in many investigations. To reduce the nonlinear errors caused by the Kalman filter (KF) while linearizing, it was proposed to use a GA-optimized BPNN. Using the dynamic stress test (DST) driving cycle, the findings show that the suggested method achieves an accuracy of less than 0.0121 with very small average and maximum errors. For the purpose of assessing battery health using GA, Hu *et al.* [41] presented a novel approach. In order to understand the structure of the model, a clustering technique was used. Results demonstrate that the estimator outperforms alternatives based on more conventional modeling approaches. With GAs, we can optimize charging and discharging processes, as well as EV resource allocation and battery arrangement optimization.

4.2 Lightning Search Algorithm (LSA)

Taking its cue from lightning strikes, LSA is a meta-heuristic method. An SOC estimate model for lithium-ion batteries that utilizes the LSA optimization approach was presented by Hannan *et al*. [42]. The methodology surpassed other state-of-the-art methodologies in terms of accuracy, flexibility, and robustness across various operating situations, according to the findings. When time is of the essence, LSA's ability to quickly converge on optimum or nearly optimal solutions makes it a powerful tool. It efficiently manages high-dimensional search regions and dependably works on a large number of optimization jobs. On the other hand, when dealing with complicated, multimodal problems, LSA has several limitations. Furthermore, LSA could not achieve the same level of success in balancing exploration and exploitation.

4.3 Particle Swarm Optimization (PSO)

PSO is a population-based metaheuristic optimization technique inspired by the cooperative actions of groups of animals, such as fish or birds. By modeling the motion and interaction of individual particles in a multidimensional search space, this technique is used to find the best solutions to optimization issues. Lipu *etal.* [43] estimated the SOC of lithium-ion batteries using a PSO-based model known as the nonlinear autoregressive network with exogenous inputs (NARX).Using three distinct temperatures and several EV driving cycles, we assessed this model's durability. With a 53% decrease in RMSE and a 50% reduction in MAE, the suggested model outperforms a single NARX method in terms of time and accuracy estimates, respectively.In order to evaluate the SOC and SOH of lithium-ion batteries online, Li *et al.* [44] suggested a PSO-based model. The SVM's kernel performance was improved with the help of PSO. Tests like the DST showed a lot of potential and adaptability. Adding PSO to EV BMS has several benefits, such as longer battery life, better resource management, and the capacity to find and use solutions from a large search area. PSO's simplicity, user-friendliness, and capacity to efficiently find solutions in high-dimensional spaces without gradient information make it a powerful tool.

4.4 Whale Optimization Algorithm (WOA)

The new Whale and Dolphin Awareness (WOA) program takes its cues from nature and the social behavior of humpback whales. By determining the best battery properties using WOA, Wu *et al*. [45] presented a technique for predicting SOC that improves the accuracy of the estimations. There are benefits and drawbacks to using the Whale Optimization Algorithm. WOA's simplicity and user-friendliness have made it famous. It works well for many optimization issues because it strikes a good mix between exploitation and exploration. Because of its exploration methodology, WOA is able to tackle both continuous and discrete optimization problems, and it is particularly good at discovering global optimum solutions. Its chances of being trapped in local optima are likewise diminished. Its reduced number of control settings means less fine-tuning is required.

Table-3. Review of optimization techniques for advanced BMS applications.

Optimization Technique	Target	Advantages	Disadvantages
GA	SOC SOH	• Successful in expanding globally. • Robustness to the noisy data. • Versatility.	• A challengeto managing limitations. • Complexity and computation.
LSA	SOC	• Robustness • Interoperability • Adaptability	• Parameter dependency. • Low convergence speed. • Tuning complexity.
PSO	SOC SOH	• Adaptability • Interpretable results • Multi-objective optimization	• Restricted multimodal search. • Handle noisy data with difficulty. • Sensitivity of parameters.
WOA	SOH	• Processing in parallel. • Possibility of an innovative solution.	• Limited thorough research. • Difficult to implement. • Absence of broad adaptation.

5. RULE - BASED APPROACHES

5.1 Fuzzy Neural Network (FNN)

Fuzzy logic networks (FNNs) are a kind of hybrid computational model that incorporates both fuzzy logic and neural networks. Combining neural networks' learning powers with fuzzy logic's reasoning and decision- making abilities, it tackles complicated circumstances marked by ambiguity, imprecision, and incomplete information.There are a number of benefits and drawbacks to fuzzy neural networks, which integrate artificial neural networks with fuzzy logic.Their versatility in dealing with imprecise and ambiguous data makes them well-suited for applications including pattern recognition, control systems, and decision support. Fuzzy neural networks are great at managing dynamic and non-linear systems because they can detect intricate relationships in data and adapt their models over time. Additionally, they may include reasoning that is comparable to human logic, which makes the findings easier to grasp and interpret, a crucial quality in situations that need openness. The downsides of fuzzy neural networks should not be

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overlooked, however. Their computational demands stem from the large amounts of computing power that may be needed for training and inference. A SOC estimation model was created by Zahid *et al*. [46] using a neuro-fuzzy system with subtractive clustering. The suggested model was tested in a state-of-the-art vehicle simulator. Current temperature, cooling air temperature, actual power loss, requested and available power, and battery thermal factor were all inputs into the model that calculated the state of charge. The training and testing verification process made use of ten distinct EV driving cycles.The experimental findings show that the suggested model is superior to BPNN and ELM.

5.2 Fuzzy C-Mean (FCM)

When dealing with fuzzy or soft clustering situations, where data points might belong to several groups with varying degrees of membership, FCM- a technique that improves upon the traditional K-Means clustering method-is useful. Sorting data into sets according to shared characteristics is a typical use of this method. In their work, Hu *et al*. [30] presented an evolutionary algorithm-based fuzzy C-means clustering technique.We can learn about the model's parameters and topology from the clustering results. Next, we use the recursive least-squares method to get the parameters. Remarkable precision and resilience are achieved by optimizing prior data and subsequent sections using the backpropagation learning approach. The experimental findings show that compared to traditional fuzzy modeling methods, the suggested approach performed better.

6. FUTURE RESEARCH OPPORTUNITIES

When BMS wants to do its job well, it needs reliable estimates of various battery states, including SOC, SOH, and RUL. Overcharging, over discharging, and overheating might occur as a result of an incorrect SOC forecast. Also, the capital cost would go up if consumers had to wait for the battery to fail or replace it beforehand, since the SOH and RUL estimates weren't correct. There has to be further study using DL algorithms to improve the BMS's accuracy, robustness, and dependability in EV applications. Improve operational efficiency and reduce computing complexity in the BMS by using multi-scale and co-estimates to make battery SOC, SOH, and RUL estimations more accurate.

Results are better when AI and BMSs work together than when non-hybrid algorithms are used alone. However, serious mathematical calculations, trustworthy processing, and human knowledge may be necessary for AI integration with an optimization model, which might lead to undesirable outcomes. Therefore, in order to create a workable hybrid paradigm for BMSs, future research should concentrate on practical considerations.

Experiments have often validated AI algorithms. We still haven't figured out how to run AI algorithms with minimum memory and resource consumption. Therefore, in order to improve battery testing systems and include, monitor, and evaluate real-time algorithms into BMS, more research into hardware-in-the-loop or embedded prototype systems is required.

By combining big data platforms with cloud technologies, BMS that rely on AI algorithms may be made much more effective. To evaluate the efficacy and accuracy of the AI algorithms, real-time measures from EVs like voltage, current, and temperature may be gathered.

7. CONCLUSIONS

This research delves deeply into the BMS statistical evaluation of EV-based AI systems, including a wide range of AI techniques, results, difficulties, and potential avenues for further investigation and improvement. Current publishing patterns, renowned authors, research categories, networking, cooperation, citation, and keyword analytics were all part of the study. While reviewing important algorithms and approaches from reputable literature, the study outlined its primary results, contributions, strengths, and shortcomings. Additional research and improvements to the sector were suggested in the study's conclusion.

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