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Review Article

Comparative Analysis of Various Optimization Techniques for Battery Management Systems in Electrical Vehicles

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Abstract: Advancements in technology have prioritized renewable energy (RE) and reduced the negative environmental impacts of transportation. This has stimulated the development of artificial intelligence (AI) techniques for efficient public transportation systems. The main challenge in developing electric vehicles (EVs) is minimizing energy consumption and charging time, and maximizing battery life compared to traditional transportation. An optimization of the battery management system (BMS) is required to improve the performance, efficiency, and reliability of EVs. This paper studies the comparative analysis of different optimization techniques for BMS in EVs. The comparative analysis of optimization approaches is explored based on the appropriateness of simulation, real-time implementation, computational complexity, and the capability of optimization. The combination of two techniques, such as, machine learning and user-centric design, provides the best response for BMS in EVs. The hybrid technique accelerates the shift to sustainable mobility solutions and enables the full potential of EVs in order to minimize their ecological impact. The computational cost and uncertainty challenges for EVs can be minimized in further research.

Keywords: Optimization techniques, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Neural Network (ANN), Fuzzy Logic Controller (FLC), Battery Management System (BMS) and Electric Vehicles (EVs).

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NOMENCLATURE

AI	Artificial Intelligence
ANN	Artificial Neural Network
BA	Bat Algorithm
BESA	Bald Eagle Search Algorithm
BESS	Battery Energy Storage System
BLDC	brushless DC
BMS	Battery Management System
CO_2	Carbon dioxide
DG	Distributed Generation
DR	Demand Response
ECMS	Equivalent Consumption Minimization Strategy
EHs	Energy Hubs
EMS	Energy Management Strategy
ESS	Energy Storage Systems
EVs	Electric Vehicles
FA	Firefly Algorithm
FLC	Fuzzy Logic Controller
FPGA	Field-Programmable Gate Array
GA	Genetic Algorithm
HEV	Hybrid Electrical Vehicle
HHO	Harris Hawks Optimization
IoT	Internet of Things
LCOS	Levelized Cost of Storage
MF-FNN	Multilayer Feed-forward Neural Network
MOSO	Multi-objective Snake Optimization

MPC	Model Predictive Control
PCB	Passive Cell Balancing
PLs	Parking Lots
PI	Proportional Integral
PMS	Power Management System
PSO	Particle Swarm Optimization
RE	Renewable Energy
RES	Renewable Energy Source
R-KM	Runge-Kutta Method
SDHO	Smart Decision Hunting Optimization
SoC	State of Charge
SoH	State of Health
TD (λ)	Temporal Difference
TES	Thermal Energy Storage

1. INTRODUCTION

Conventional vehicles produce environmental pollution due to fossil fuels such as diesel, petrol, etc. In recent technology, EVs offer a valuable solution to reduce environmental pollution and save fossil fuels in transportation. Battery banks are used in EVs which are an important part of them. It manages essential functions such as State of Charge (SoC) estimation, thermal management and cell balancing [1]. These functions are very important for the long-term performance and durability of vehicles. Intelligent-based control methods used for BMS in EVs which were explored to address challenges and investigate further opportunities [2]. In this regard, the intelligent control method, as an interval type-2 FLC-based optimization technique, controls energy management in plug-in hybrid EVs. The impact of air conditioning frameworks under altering environmental temperatures is discussed, and it minimizes energy consumption, increases thermal safety, and comfort [3].

The study of novel hybrid and co-estimation methods is employed in order to calculate the State of Health (SoH) that is useful in BMS for EV systems [4]. The digital twin model is used for BMS based on historical data in order to diagnose battery banks [5]. The BMS of EVs is responsible for controlling the battery banks which produce a driver to control the high performance of systems. It is the unit of electronic control that supervises the battery system in the EVs. Using BMS technology, it manages the SoH, performance and safety of the battery setup [6].

The essential features of BMS are designed for EVs, such as controlled voltage, current, and temperature to ensure the safety of battery operation. It prevents battery damage from overheating, overcharging, and over-discharging and also helps extend battery life by balancing individual cells. The main component of the battery relay is that it helps the SoH and SoC of the EV. It is valuable for accurate range estimation and optimal performance of EVs.

Fig. 1 illustrates the powertrain for the framework of the EV battery. It is driven by a single source of energy, such as a traction battery. The main motive of the battery is to have a large capacity and maximum output power. The battery setup of an EV has two operating modes (such as charging and discharging modes). In discharging mode, it powers the electric motor that converts the electrical energy into mechanical energy. This mechanical energy drives the rotational energy to the wheels of the EVs. Also, the battery setup provides power to other onboard systems such as air conditioning, sensing, communication, and infotainment facilities [7-9]. This power can be obtained from RE sources using the Internet of Things (IoT) based optimization techniques [10]. In order to propose a new algorithm of Smart Decision Hunting Optimization (SDHO) which is to optimize the charging process for EVs. This technique produced the optimum response as the best, fastest, and accurate charging stations, and it also reduces waiting time and energy consumption. The SDHO technique takes the average waiting time and distance to charging stations. The main aim is to minimize the factors and to provide the best possible charging. The results of this technique show better performance in terms of charging speed, waiting time, and energy efficiency as compared to the specified existing methods. This technique makes it a good solution for enhancing the charging system for EVs [11]. A new Energy Management Strategy (EMS) has been proposed which is to improve the fuel efficiency of hybrid vehicles. This method consists of computer vision and deep reinforcement learning which helps to use its best power for learning about the EVs. Using this method, the authors are tested based on four different types of hybrid vehicles. It was found that it can significantly improve fuel efficiency as compared to existing control methods. This technique is faster and more reliable than other deep learning-based strategies. It is clearly seen that computer vision and deep learning can be valuable tools for developing more efficient and sustainable hybrid vehicles [12]. Fig. 1 represents the schematic diagram of the optimization techniques for a BMS in an EV. In this schematic diagram, each module is shown as a block, and arrows indicate the information and control flow between modules. In this research article, in order to compare the study of various optimization techniques for BMS in EVs. It emphasizes their consequence of obtaining optimal performance of the battery and improving the global driving experience. The following points are highlighted in favour of optimization techniques for BMS in EVs.

- To compare various optimization techniques for BMS in EVs in terms of appropriateness of simulation and real-time implementation.
- To achieve effective power delivery and accurate SoC estimation, controlled in order to achieve a longer driving range per charge.
- To support cell balancing and thermal management techniques to reduce degradation factors and extend battery lifespan.
- To actual monitoring and control to prevent over-charging, over-discharging and overheating of the battery during operation of EVs.

The manuscript is structured as follows: Section 2 provides an overview of various optimization techniques used for BMS in EVs. Section 3 discusses the comparative analysis of optimization techniques for BMS in EVs. Section 4 explains the future scopes of the study, and finally, conclusions are presented in Section 5.

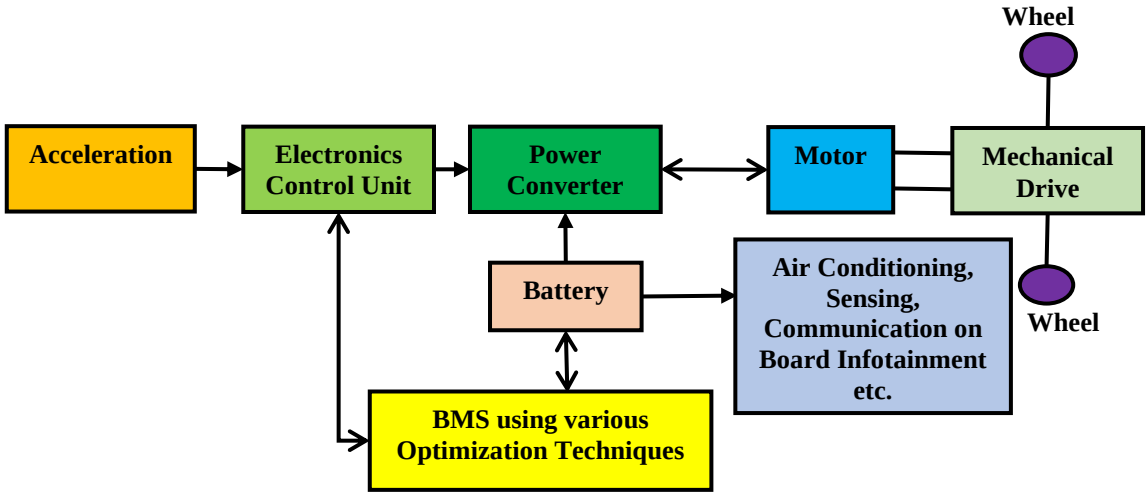


Fig. 1: Schematic diagram of the optimization techniques for a BMS in an EV.

2. Overview of Optimization Techniques for BMS in EV

The flowchart illustrates the flow of information and control within the BMS of the EVs which highlights the interaction between input signals, state estimation, optimization techniques, decision-making, and output commands [13]. The optimization techniques used by the BMS can effectively manage the operation of the battery pack, optimize energy utilization and ensure the safe and reliable performance of the EVs [14]. Fig. ***2*** shows the flowchart of optimization techniques in terms of various modules for BMS in EVs.

The following steps are described in various modules. The input module receives input signals (such as voltage, current, temperature, and SoC of battery banks) from various sensors which are installed within the EVs.

In the state estimation module, this module utilizes received input signals which is to estimate the current of SoC, SoH and other relevant parameters of the battery pack using mathematical models. The control module implements optimization techniques to manage the operation of the battery banks. This module governs charging and discharging processes, cell balancing, thermal management and other control techniques which maximize the performance and lifespan of battery banks. The optimization technique module is a module that contains different optimization techniques such as rule-based algorithms, model predictive control, GA, PSO, ANN, FLC, etc. Each technique is tailored to specific optimization objectives and constraints such as energy efficiency, thermal safety, and battery longevity. The decision-making module analyzes data from the state estimation module and optimization technique to make informed decisions regarding battery operation. This module determines the optimal charging and discharging rates, temperature limits, and other control parameters based on predefined rules, optimization algorithms and user-defined preferences. The output module is used to send the control signals and feedback to the BMS and also other vehicle subsystems, which are to execute the determined control techniques. This module can be used for the proper implementation in favour of optimization methods and the

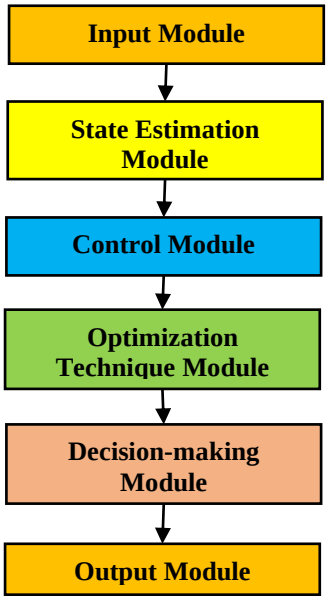


Fig. 2: Flowchart of various modules for optimization techniques.

control decision module is used to maintain the health and performance of battery banks.

Fig. 3 illustrates the flowchart of the novel SDHO optimization technique for the BMS in the EVs [11]. This proposed method explores the search space to investigate promising regions. It targets decontaminating solutions within specific regions. This method also maintains a balance between exploration and exploitation which is to avoid getting stuck in local optima.

The focus of researchers is optimizing energy management, improving efficiency and reducing operational costs of hybrid EVs. To minimize energy losses and produce a stable power supply using the concept of RE sources which are integrated with vehicle-to-grid technology. A machine learning approach is specifically TD (λ) learning that is used to determine the optimal charging and discharging technologies for hybrid EVs. This assists in extending battery life and reduces the necessity of frequent replacements. The results demonstrate that the proposed optimization method can significantly reduce operational costs and extend battery

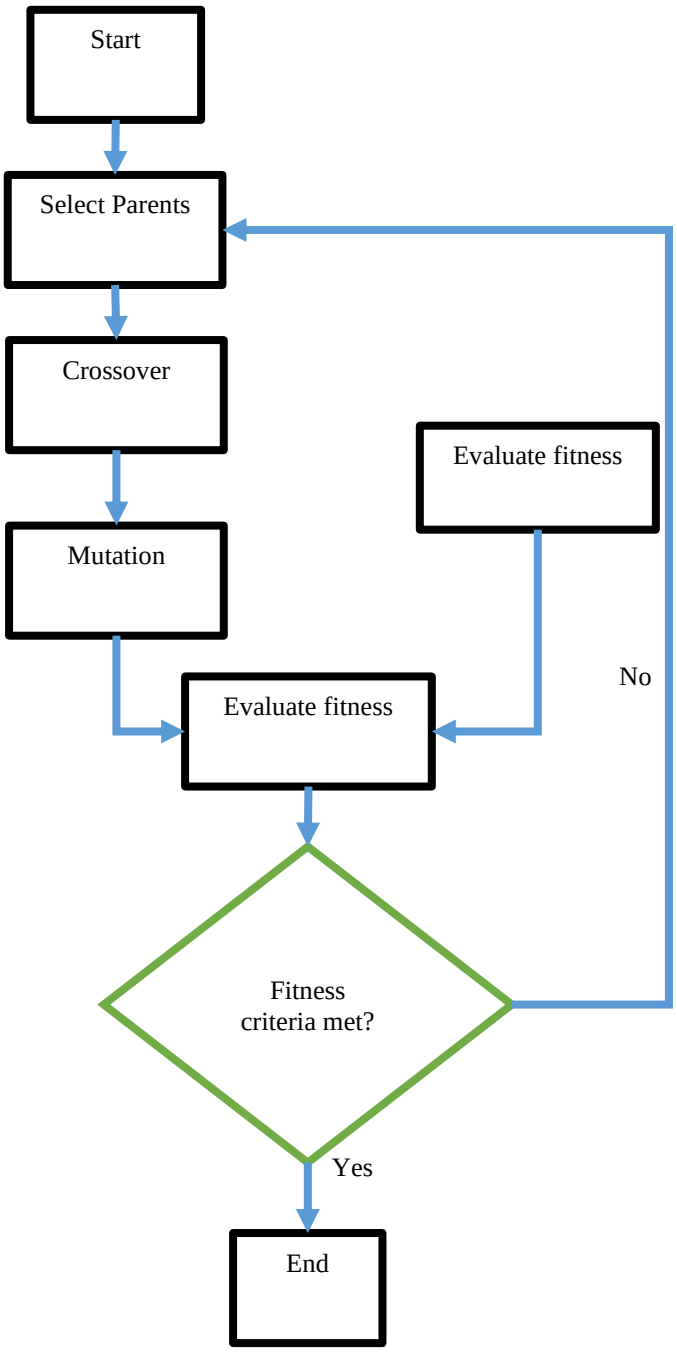


Fig. 3: Flowchart of novel SDHO optimization techniques.

life. Using optimizing energy management-based technique that the hybrid vehicle can operate more efficiently which leads to lower fuel consumption and lower emissions [15].

Elkholy et al. [16] proposed a three-level AI-based EMS for isolated microgrids. It consists of three phases. The first phase represents a field-programmable gate array (FPGA) used for fast response. The second phase represents a Multi-objective Snake Optimization (MOSO) technique employed to reduce operational costs, energy losses and reliability of power supply. In the third phase, the hybrid optimization technique consists of a multilayer feed-forward neural network (MF-FNN) and MOSO which is used to predict the output response of the battery for EVs. The proposed MF-FNN-MOSO technique improves the efficiency and reliability of the microgrid which achieves the best performance in predicting the output power of battery backup and reducing operational costs. EVs are frequently increasing in the market to reduce environmental impact. Though the charging process of EVs can put a strain on the power grid. One solution is to aggregate EVs in parking lots (PLs) and manage their charging collectively. Proposed optimization model for smart PLs to minimize power drawn from the grid while meeting customer needs. The model considers both single and 3-phase EVs and uses a non-linear battery charging profile. An augmented Lagrangian-based decentralized model predictive control technique is used to solve the optimization problem. The proposed method has been tested on smart PLs in Genova, Italy, and is efficient and accurate, even when scaling up to 40 EVs [17]. The predictive flex smoother method is proposed by Benavides et al. [18]. This method mitigates power fluctuations in the grid-connected PV framework, although it optimizes energy management in EV charging stations. The proposed method effectively improves power quality and reduces costs. Real-time testing has shown response times under 500 ms. The method efficiently handles power smoothing and charging strategies for diverse EV models and connection coefficients. Researchers proposed an energy management system for residential buildings that optimizes energy flow, energy storage systems (ESS) parameters and energy consumption scheduling in order to minimize costs, extend ESS lifespan and reduce CO_2 emissions. The system integrates Renewable Energy Sources (RES), ESSs, and EVs, and utilizes demand response (DR) programs to optimize energy usage. The optimization technique considers factors like installation costs, levelized cost of storage (LCOS), seasonal variations, energy consumption profiles, and energy prices. The results demonstrate significant cost reductions, energy loss reductions and extended EV battery life, leading to substantial financial savings and environmental benefits [19]. Fig. 4 shows the energy flow management algorithm for EVs.

The fitness function of the GA is determined as the inverse of the total distance + waiting time penalties and exceeding distance penalties [20].

Formulation of the fitness function

$$F = \frac{1}{f} \tag{1}$$

$$f = w_1 \sum_{k=1}^{N} d_i + w_2 \sum_{k=1}^{N} q_i + w_3 P \tag{2}$$

where d_i represents the distance travelled between consecutive stopes on the route, and q_i represents the waiting time at the charging station at i. P represents the exceeded distance penalty, and w_1, w_2, and w_3 represent the weight factors.

$$q_i = \begin{cases} actual\ queue\ time & if\ station\ is\ in\ the\ cluster \\ average\ queue\ time & otherwise \end{cases}$$

In the other way, the droop control technique is a way of control the output power of generator in a power system. It is used to maintain the balance of power between generators when availability of parallel connections of multiple generators. The basic equation for a droop control system is as presented in (3).

$$Gen_{output\ Power} = P_{bo} \times (1 + Droop_1) \times \left(\frac{F_d}{F_{bd}}\right) \tag{3}$$

where, P_{bo}= base output power (rated power output of the generator at a reference frequency (F_r = 50Hz), F_d=frequency deviation, F_{bd}= frequency deviation at base power and $Droop_1$ is the percentage power drop per unit of F_d form F_r [21].

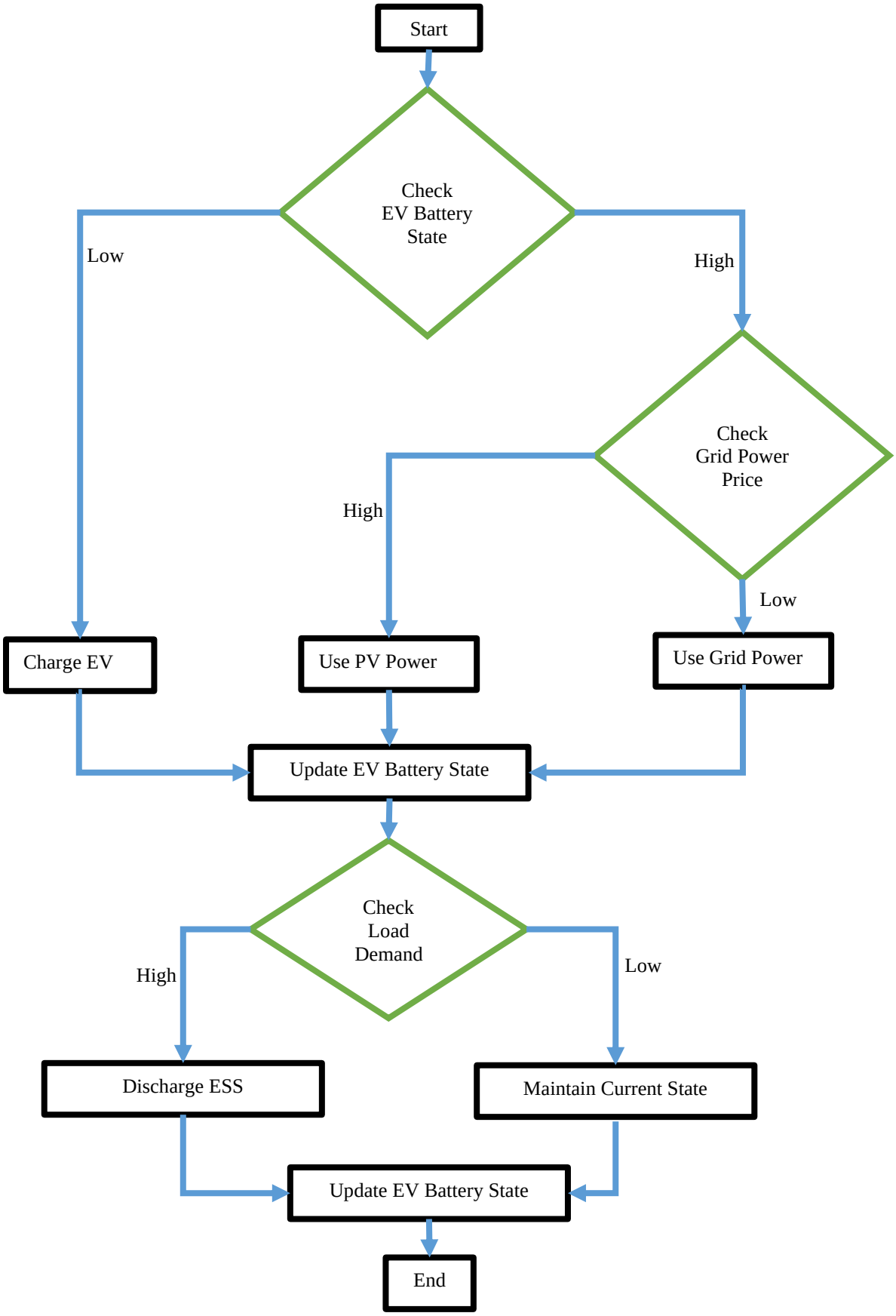


Fig. 4: Flowchart of energy flow management algorithm.

Fig. 5 represents the flowchart of a basic integration of RES and EVs using FLV and GA. It considers factors including RES available, EV battery state, load demand and optimization of energy flow [22].

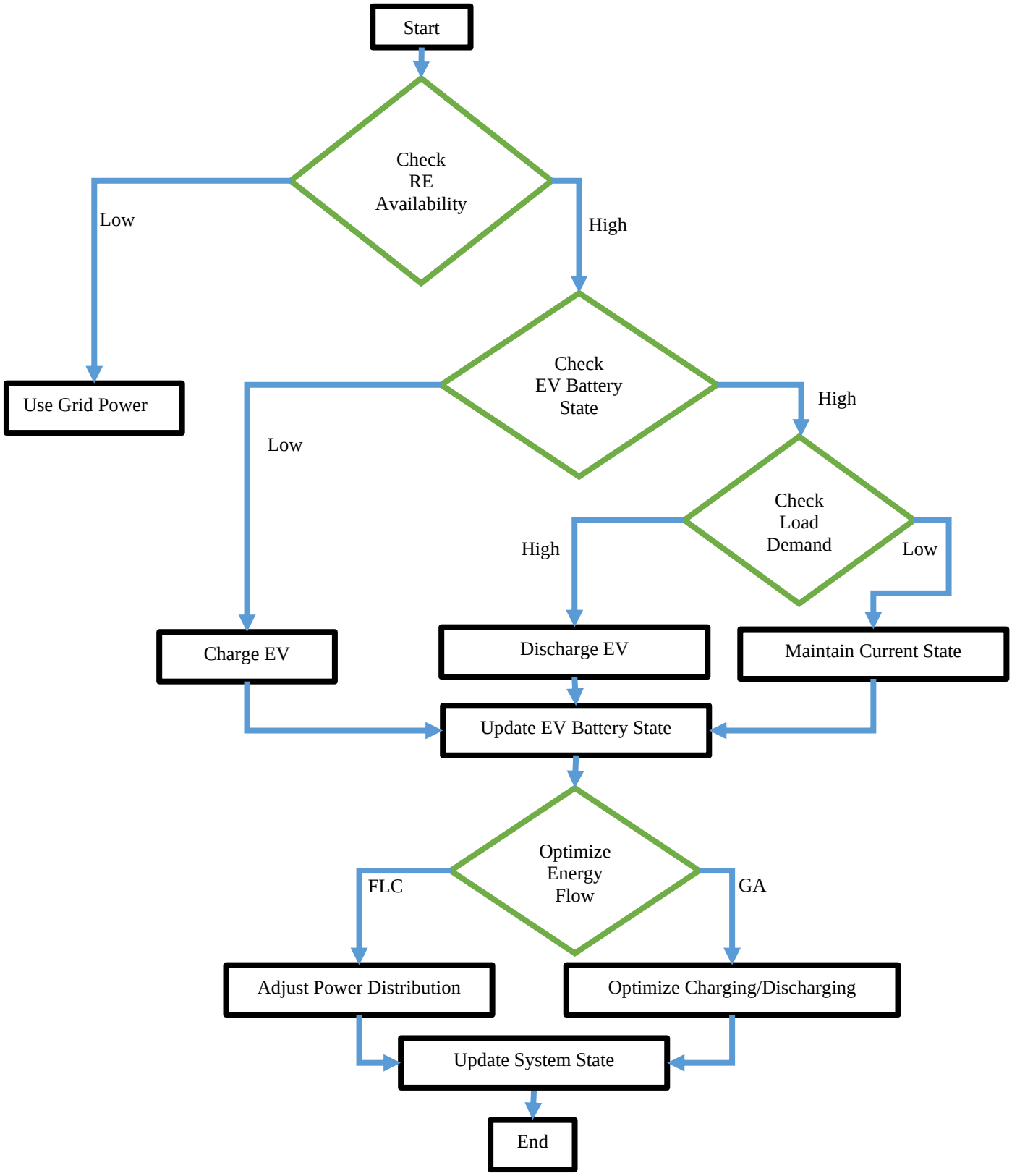


Fig. 5: Flowchart of a basic integration of RES and EVs using FLC and GA.

Fig. 6 represents the flowchart of the extraction of maximum power from solar with brushless DC (BLDC) motor-driven EVs-based Harris Hawks optimization (HHO) algorithm. HHO offers MPPT for solar PV-powered EVs. This proposed MPPT approach outlined that it enhances overall efficiency and reduces operational costs for EVs using the PV framework [23]. Authors have investigated the inclusive analysis of hybrid EV (HEV) components including their construction, mathematical models and methodologies [1]. Kandil et al. [24] examined optimization approaches for fast charging stations' allocation and size. An in-depth examination and critique of the placement of EV charging stations within distribution networks [25].

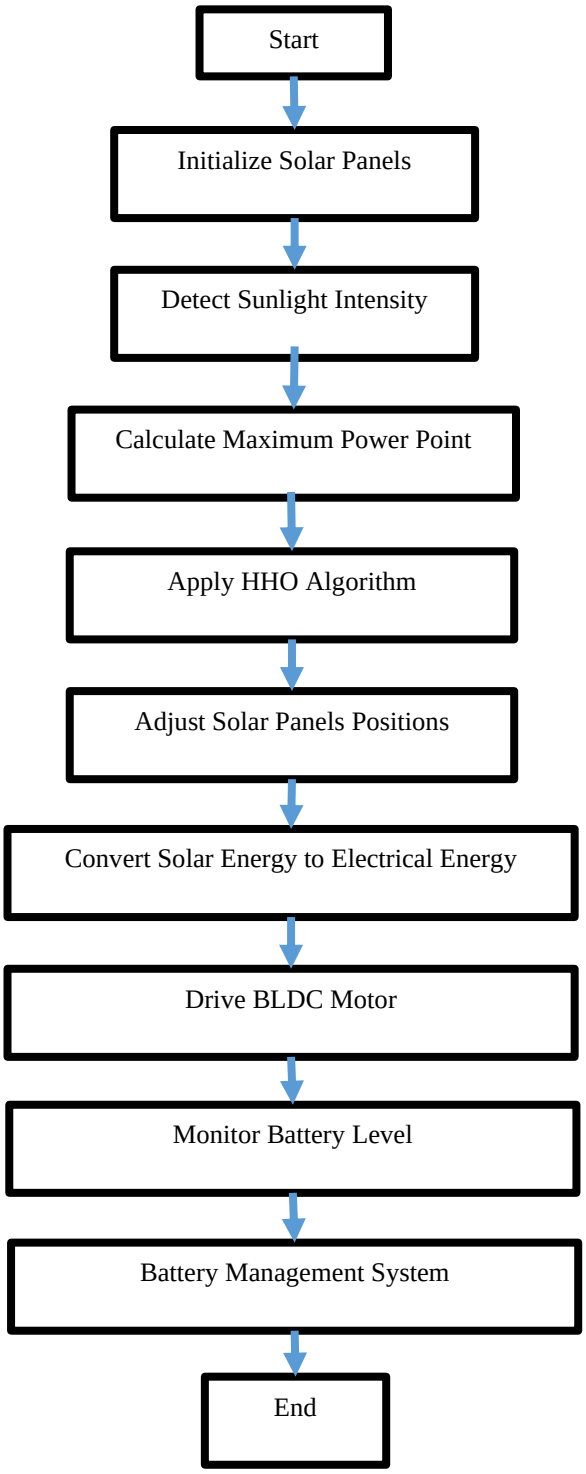


Fig. 6: Flowchart of Extraction of maximum power from solar with BLDC motor driven EVs based HHO algorithm.

The pinch analysis-based optimization technique is a systematic procedure for finding simultaneous sizes for the EES and thermal energy storage (TES) framework to yield suitable sizes for fuel cells, battery radiators, and TES materials [26]. Energy hubs (EHs) are vital for sustainable energy. This emphasizes a residential EH that effectively harnesses different energy sources and technologies to meet domestic needs. The main aim is to develop an efficient heat and power management system (PMS) that minimizes operational costs. Data-driven techniques and advanced forecasting methodologies are used to enhance the efficiency of frameworks. The results show that these techniques can significantly reduce power costs in the EH scheme [27].

The dynamic EV model is examined by using the 4th-order Runge-Kutta method (R-KM) to assess its performance under different driving situations. The results indicate that the dynamic EV model offers a structured approach to simulate and optimize complex EV systems [28]. Manivannan [29] proposed a machine-learning approach to create a smart energy management framework for hybrid EVs with energy storage as battery banks. This proposed framework can optimize energy usage, reduce operational costs, and prevent overloading the electrical grid.

This study implements an IoT-based smart charging framework in order to enable more precise control and also improve the efficiency of the system. The main aim of the proposed algorithm is to reduce power loss, voltage deviation and charging station costs while maximizing traffic flow and satisfying EV requirements. It focuses on the optimization of the existing grid infrastructure to meet the requirements of EV users, the transportation network and the energy distribution network [30]. It was implemented in MATLAB and compared to other existing methods. It produced better performance in terms of accuracy and computational efficiency. The proposed method had the lowest error (i.e. 4 mV) and the shortest computation time (i.e. 0.7 s) [31].

A new Proportional Integral (PI) and an ANN-based controller are developed to manage Passive Cell Balancing (PCB) technology for BMS in EV [32]. Machine learning-based EV charging is implemented with an optimized flyback converter for solar PV frameworks [33]. Optimization of EV charging station placement using PSO in Smart Grids [34]. The proposed strategy for reducing power loss was tested on Indian 28-bus and 108-bus distribution networks. The results showed that the bald eagle search algorithm (BESA)-based optimization method outperformed the bat algorithm (BA) based method in terms of power loss reduction, voltage improvement, and overall cost savings [35]. Elazaib et al. [36] presented three novel smart home energy management algorithms which are designed for developing countries. These algorithms focus on load shifting, vehicle-to-home energy transfer and reduced air conditioning, considering factors like battery life, user comfort and local climate conditions. This study also evaluates the economic feasibility of integrating solar PV arrays. The proposed energy management scheme can significantly reduce electricity bills by up to 61%.

The authors compare four residential load scenarios to assess the economic and environmental benefits of integrating EVs into microgrids. A control technique is introduced to optimize battery energy storage system (BESS) charging and discharging based on time-of-use pricing and EV power. Two optimisation algorithms are compared to assess the effectiveness of the control technique. The results demonstrate that controlled EV integration can reduce costs by \$0.728 million and CO_2 emissions by 213.23 kg. Controlled BESS integration reduces costs by \$0.835 million and CO_2 emissions by 360.68 kg. The semi-isolated microgrid configuration offers the lowest overall cost at \$1.421 million [37]. The primary objective is to minimize energy and thermal discomfort costs over a long-term horizon in a sustainable smart home while considering factors such as

occupancy, temperature preferences, electricity consumption, renewable energy generation, outdoor temperature, and electricity prices [38]. Aoumari et al. [39] proposed an energy management system that optimizes the performance of onboard electrical sources by carefully selecting the sharing filter cut-off frequency. This selection considers factors like effective power, state of charge variation, and battery cycle life. Simulations in MATLAB demonstrate the superiority of the proposed system compared to conventional methods. Koltsaklis et al. [40] proposed a smart home energy management system that optimizes energy usage and minimizes costs. The system considers factors like demand response, renewable energy integration, and energy storage. A hybrid forecasting model is used to predict energy prices and renewable generation. The results show that the system can effectively reduce energy costs and improve energy efficiency. The proposed framework can help reduce the strain on the power grid, especially in developing countries [41]. The results illustrate that the proposed optimization method is compared to other existing specified techniques. It can be used to assess the reliability of electrical distribution networks. This study concludes that integrating the approach of distributed generation (DG) and EVs can enhance the reliability of the electrical system [42].

Researchers have investigated the impact of energy consumption budgets in various aspects of operational vehicles, including fuel consumption, electric motor usage, gear shifting strategy, and engine parameters like intake manifold pressure, air-fuel ratio, and turbine waste-gate position [43]. Ajayan et al. [44] proposed an optimized method, which is used to determine the optimal size of fuel cells and battery banks. PSO and the Firefly Algorithm (FA) are used to calculate the optimal solution for BMS in EVs. In this regard, various constraints are considered, such as the battery's state of charge and the fuel cell's rating, while also accounting for replacement costs. The results demonstrate that the FA optimization algorithm provides better performance in terms of cost reduction, population size and convergence speed. An innovative approach to controlling the charging and discharging processes in battery management operations using a bidirectional converter [45].

Yamini et al. [46] compared the fuel consumption of a hybrid vehicle under different driving cycles using the Equivalent Consumption Minimization Strategy (ECMS). The goal of this method is to determine the optimal strategy in order to minimize fuel consumption and improve the performance of the vehicle. The findings can contribute to the development of sustainable hybrid EVs. Yammani et al. [47] proposed optimizing EV charging and discharging to maximize EV owner profits and support grid operations. This technique considers factors such as energy prices, state of charge of the battery, and RE availability. The results illustrate the effectiveness of the proposed approach in improving grid reliability and reducing costs. An economic analysis is carried out on the PV framework under peak load scenarios of the electric power distribution framework, considering the impact of EVs [48]. To study presents a reliability evaluation of power systems that incorporate pumped storage units. It developed a reliability model to assess the impact of component failures on complete framework adequacy [49]. This work focused on efficient demand response and robust voltage control in an islanded DC microgrid. The study addresses challenges arising from alterations in both load and supply [50].

3. COMPARATIVE ANALYSIS OF OPTIMIZATION TECHNIQUES FOR BMS IN EV

A comparative study of various optimization techniques for BMS in EVs is an important endeavour, given the critical role of BMS in terms of the safety and longevity of EV batteries. Table 1 represents a concise analysis of optimization techniques.

Researchers have investigated and analyzed various optimization techniques for BMS in EVs. The literature shows that there are several optimization techniques available for BMS in EVs. Various optimization techniques are investigated, and advised machine learning methods like ANN are used instead of traditional rule-based algorithms. The diverse range of techniques highlights the complexity of the optimization difficulty and the necessity for customized results for various application scenarios. When it comes to optimization approaches, there is a trade-off between speed and complexity. Rule-based algorithms are faster and can be used in real-time applications. Still, improvement is required for the adaptability and capabilities of proposed frameworks such as predictive control models and ANN technologies.

Advanced optimization techniques like model predictive control and GA have improved battery efficiency and lifespan performance. Though, it often requires higher computational costs, posing challenges for real-time implementation in recent technology-based EVs. Many researchers have explored hybrid technologies combining more than two optimization techniques to reduce their limitations. For example, a combination of two approaches of machine learning models and rule-based algorithms can control the simplicity of rules and the learning capabilities of ANN simultaneously. The accuracy of battery banks is important when using optimization techniques. In order to achieve optimal performance of BMS, it is essential to ensure that the battery setups are accurate using data-driven and parameter estimation technologies. Optimization techniques are implemented in EV systems in the real world due to challenges in achieving desirable results in theoretical studies and simulations. Several factors including computational complexity, robustness against uncertainty and scalability for large-scale EVs, are addressed for practical deployment.

4. FUTURE DIRECTIONS

The optimization techniques are used for BMS in EVs due to challenges in favour of enhancing the performance, efficiency, and reliability of frameworks. There are some important findings for future work.

Table 1: Comparative analysis of optimization techniques for BMS in EVs.

Ref.	Optimization Technique	System	Converge-nce Speed	Computational cost	SoC/ SoH accuracy	Real-time applicab-ility	Benefits	Research Gaps
[51], [52]	Rule-Based Algorithm	Traditional BMS	Fast	Very low	Moderate to low	Highly suitable	• Simplicity and ease of implementation. • Real-time operation suitable for simple applications.	• Limited adaptability to dynamic operating conditions. • Lack of optimization for long-term battery health. • May not fully exploit the potential of advanced battery chemistries.
[53], [54]	Model Predictive Control (MPC)	Advanced BMS	Moderate	High	Higher SoC estimation accuracy and improving long term battery health management	Challenging for embedded BMS hardware	• Optimization based on predictive battery models. • Accommodates dynamic operating conditions and constraints. • Improved energy efficiency and battery lifespan.	• Computational complexity and requirement of accurate battery models. • Limited scalability for large-scale EV fleets. • Challenges in real-time implementation for highly dynamic environments.
[55], [56]	GA	Adaptive BMS	Moderate to Slow	Computationally intensive	High	Limited Realtime feasibility	• Exploration of a wide solution space to find optimal parameters. • Adaptability to varying operating conditions and battery chemistries.	• High computational overhead, especially for complex battery models. • Difficulty in fine-tuning algorithm parameters for specific applications. • Limited transparency in the decision-making process compared to rule-based approaches.
[57], [58]	PSO	Adaptive BMS	Moderate	High	High	Slow	• Efficient exploration of solution space through swarm intelligence. • Rapid convergence to near-optimal solutions. • Suitable for real-time implementation in dynamic environments.	• Sensitivity to initial parameters and swarm size. • Limited robustness in noisy or uncertain environments. • Challenges in balancing exploration and exploitation for complex optimization problems.
[55], [59], [60]	ANN	Intelligent BMS	Moderate to Slow	Moderate to high	High	Feasible	• Adaptive learning and ability to capture complex nonlinear relationships. • Improved accuracy in prediction and control compared to traditional methods.	• Training data availability and representativeness. • Interpretability and explainability of model decisions. • Computational overhead and hardware requirements for real-time implementation.
[61]	FLC	Intelligent BMS	Fast to Moderate	Moderate	Low to moderate	High	• Linguistic rule-based approach suitable for handling uncertainty and imprecision. • Intuitive modelling of human expertise and decision-making.	• Difficulty in defining fuzzy sets and membership functions. • Limited scalability for complex systems and large-scale optimization. • Challenges in integrating fuzzy logic with other optimization techniques for hybrid approaches.

1. To explore the integration of advanced deep and reinforcement learning for optimization of BMS in EVs. This hybrid technique can improve accuracy and optimize control in dynamic environments with varying operating conditions.
2. To develop optimization algorithms and control strategies with practical feasibility and scalability which is suitable for real-time implementation in EVs. It can be considered for hardware constraints including processing power and memory.
3. The main objective is to improve the stability and consistency of optimization techniques with uncertainties including variable factors such as characteristics of the battery, and environmental conditions. It produces robust optimization, uncertain quantification and adaptive control in order to improve the dependability of the proposed system.
4. To investigate the hybrid optimization approaches of model predictive control with evolutionary algorithms and FLC with ANN. Additionally. It can consider multi-objective optimization frameworks in order to optimize conflicting objectives including energy efficiency, battery lifespan and thermal management.
5. To propose the optimization technique based on large-scale datasets and data-driven approaches is used to optimize battery models.
6. To develop robust validation and benchmarking of optimization algorithms, it will conduct comprehensive simulation and hardware implementation in the laboratory.
7. To maximize the global performance and efficiency of large-scale EV systems, it is important to consider scalability issues in BMS optimization. To investigate distributed optimization algorithms and decentralized control strategies for improving the results of proposed systems.
8. To improve the user experience and the adoption of EVs, that is crucial to integrate user preferences and driving behavior for BMS optimization. This can be achieved by designing intuitive interfaces and decision-support systems that offer users transparency, control and real-time response in BMS operation and battery performance.

5. Conclusion

The various optimization techniques are studied for BMS in EVs. A hybrid optimization technique is suggested to the authors to improve the response of BMS functions in EVs. It likely involves techniques that extend battery life, improve safety and increase efficiency. This study has explored various optimization approaches for BMS characteristics. To enhance the accuracy of SoC estimation in BMS, coulomb counting and Kalman filter techniques utilize data from current, voltage, and temperature. The GA and PSO algorithms help to maintain uniform voltage across all cells in the battery pack which extends battery life. Optimization techniques can be applied to control battery temperature through cooling systems, maximizing battery health and performance. It plays a crucial role in accurately estimating the SoC of an EV battery and efficiently delivering power to optimize energy usage. These methods result in a greater driving range on a single charge. Cell balancing and thermal management techniques minimize battery wear and prolong its life. Monitoring systems safeguard against overcharging, over-discharging, and overheating, ensuring the safe use of EVs.

Further research can explore the integration of advanced algorithms such as machine learning for real-time optimization and predictive maintenance of EV batteries. This advancement can lead to EVs that are more efficient, reliable and safe.

Credit Authorship Contribution Statement

Mohammad Junaid Khan: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ram Murat Singh:** Conceptualization, Investigation, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Md Naqui Akhtar:** Investigation, Methodology, Resources, Visualization, Writing – original draft, Writing – review & editing. **Asyraf Afthanorhan:** Formal analysis, Investigation, Methodology, Resources, Visualization, Writing – original draft, Writing – review & editing.

Declaration Of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

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BIOGRAPHY



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With over 14 years of experience in both Teaching and Research, Dr. Khan has demonstrated excellence in education, qualifying for the National level GATE examination and securing an impressive rank of 289 in the Madhya Pradesh Pre-Engineering Test (MP PET-2005).

His contributions to intellectual property include 02 granted Indian patents, with an additional 03 patents filed and published. He boasts a significant body of work with over 80 reputed publications, including in SCI and Scopus-indexed journals, and has also authored a book with an international publisher.

Dr. Khan's achievements have been recognized through 5 awards, including the Best Paper Award at IEEE CENCON, Malaysia, the Outstanding Scientist Award from ScienceFather India, the Best Young Scientist award from ITSR, India, and the UGC fellowship under the MANF Scheme. He has completed 04 projects sanctioned by HAREDA, Govt. of Haryana.

He is a sought-after speaker and expert, having delivered 09 Keynote addresses and served as a Technical Session Chair/Co-chair at International Conferences both in India and abroad. Additionally, he has given 05 invited lectures and served as a technical expert in various Seminars and Workshops. He has presented 17 research articles at various conferences.

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