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"RECENT ADVANCES IN GRID-CONNECTED SOLAR ELECTRIC VEHICLE CHARGING SYSTEMS: PERFORMANCE EVALUATION AND OPTIMIZATION APPROACHES"

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Abstract- The rapid adoption of electric vehicles (EVs) has significantly increased the demand for efficient, reliable, and sustainable charging infrastructure. Grid-connected solar photovoltaic (PV)-based EV charging systems have emerged as one of the most promising solutions to reduce greenhouse gas emissions, decrease dependency on fossil fuels, and improve energy security. These systems combine renewable energy generation with intelligent charging strategies to address challenges associated with increasing electricity demand, grid stability, and charging efficiency. Recent advancements in power electronic converters, bidirectional charging technologies, energy storage systems (ESS), smart grid communication, and artificial intelligence (AI)-based energy management have considerably enhanced the operational performance of solar-powered EV charging stations. This review presents a comprehensive assessment of recent developments in grid-connected solar EV charging systems, emphasizing system architectures, power management strategies, optimization techniques, and performance evaluation methods. Various optimization approaches, including classical mathematical optimization, metaheuristic algorithms, machine learning, deep learning, and reinforcement learning, are critically analyzed based on charging efficiency, computational complexity, renewable energy utilization, battery life, operational cost, and grid reliability. Furthermore, this review compares different optimization methods reported in recent literature and identifies current research gaps. The study concludes that hybrid AI-enabled optimization combined with advanced forecasting and vehicle-to-grid (V2G) technologies represents the future direction for sustainable EV charging infrastructure. The

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findings of this review provide valuable insights for researchers, engineers, policymakers, and industry practitioners involved in the development of next-generation smart charging systems.

Keywords: Electric Vehicle (EV), Solar Photovoltaic, Grid-Connected Charging System, Energy Management System, Optimization Algorithms, Smart Grid.

I. INTRODUCTION

Global energy demand has experienced unprecedented growth during the last two decades due to rapid industrialization, urbanization, and population expansion. Simultaneously, transportation has become one of the largest contributors to greenhouse gas emissions, accounting for approximately one-fourth of global carbon dioxide emissions. Conventional internal combustion engine (ICE) vehicles rely heavily on fossil fuels, resulting in severe environmental pollution, climate change, and depletion of natural resources. Consequently, governments worldwide have introduced stringent emission regulations and ambitious carbon neutrality targets, accelerating the transition toward electric mobility.

Electric vehicles (EVs) have emerged as a sustainable alternative to conventional automobiles because they eliminate direct tailpipe emissions while offering higher energy efficiency and lower operational costs. The global EV market has witnessed exponential growth over the past decade due to advancements in battery technology, declining battery costs, supportive government incentives, and increasing consumer awareness regarding environmental sustainability. According to recent market reports, global EV sales continue to increase annually, creating substantial demand for reliable and intelligent charging infrastructure.

Despite their environmental benefits, large-scale deployment of EVs introduces several technical challenges for existing electrical distribution networks. Uncoordinated charging of numerous EVs can result in significant peak load demand, voltage fluctuations, transformer overloading, harmonic distortion, increased power losses, and degradation of grid reliability. These challenges become more severe in urban regions where EV penetration is rapidly increasing. Therefore, intelligent charging strategies and renewable energy integration have become essential components of future EV charging infrastructure.

Among various renewable energy resources, solar photovoltaic (PV) technology has gained considerable attention because of its abundant availability, declining installation cost, modular design, and zero operational emissions. Integrating solar PV systems with EV charging stations enables direct utilization

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of renewable electricity, thereby reducing dependence on conventional fossil-fuel-based power generation. Grid-connected solar EV charging systems offer an attractive solution by combining the advantages of renewable energy with the reliability of utility grids. During periods of high solar irradiance, PV arrays supply a substantial portion of charging demand, whereas the utility grid compensates during low solar generation or increased charging demand.

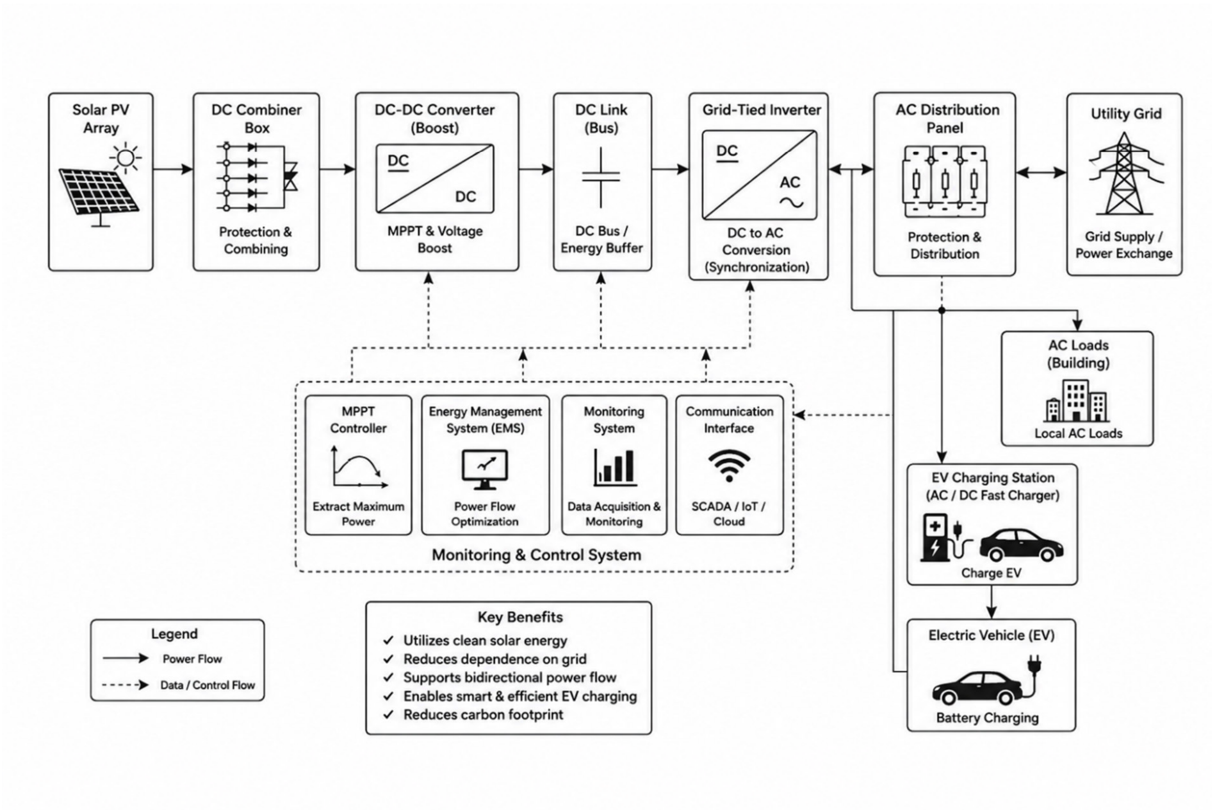

Figure 1. Solar Powered EV Charging

A typical grid-connected solar EV charging system consists of photovoltaic modules, maximum power point tracking (MPPT) controllers, DC–DC converters, DC-link capacitors, bidirectional DC–AC inverters, battery energy storage systems (optional), charging controllers, and intelligent energy management units. These components operate collaboratively to maximize renewable energy utilization while maintaining voltage stability, power quality, and charging reliability.

The integration of battery energy storage systems (BESS) further enhances charging station performance by storing excess solar energy during daytime and supplying electricity during peak demand or nighttime charging. Energy storage systems also reduce grid dependency, improve voltage regulation,

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mitigate renewable intermittency, and support ancillary grid services. Consequently, many modern charging stations adopt hybrid configurations combining solar PV, battery storage, and utility grid connections.

II. RECENT ADVANCES IN GRID-CONNECTED SOLAR ELECTRIC VEHICLE CHARGING SYSTEMS

2.1 Evolution of Grid-Connected Solar EV Charging Systems

The rapid electrification of the transportation sector has significantly accelerated research and development in electric vehicle (EV) charging infrastructure. Initially, EV charging stations relied entirely on the utility grid, resulting in increased peak demand, higher operational costs, and additional stress on distribution networks. As renewable energy technologies matured and photovoltaic (PV) system costs declined, integrating solar energy into EV charging infrastructure became a practical and environmentally sustainable solution.

Modern grid-connected solar EV charging systems utilize photovoltaic arrays as the primary renewable energy source while maintaining a utility grid connection to ensure uninterrupted charging during periods of low solar generation. This hybrid configuration enables efficient energy utilization, reduces dependence on fossil-fuel-based electricity, and enhances system reliability.

Recent charging stations have evolved from simple AC charging units to intelligent multi-energy systems capable of integrating renewable energy sources, battery energy storage systems (BESS), bidirectional converters, advanced communication networks, and artificial intelligence-based energy management platforms. These advancements have transformed conventional charging stations into intelligent energy hubs capable of interacting dynamically with smart grids.

2.2 Architecture of Grid-Connected Solar EV Charging Systems

A modern grid-connected solar EV charging system consists of several interconnected subsystems that work together to ensure efficient and reliable operation.

Major Components

Solar Photovoltaic (PV) Array

Solar photovoltaic modules convert sunlight into direct current (DC) electricity. Advances in monocrystalline silicon cells, bifacial modules, half-cut cell technology, and PERC (Passivated Emitter and Rear Contact) cells have significantly improved conversion efficiency beyond 22%.

Major improvements include:

- Higher energy conversion efficiency
- Reduced installation costs
- Improved temperature tolerance
- Longer operational lifetime
- Better performance under partial shading

Maximum Power Point Tracking (MPPT)

Since solar irradiance continuously changes throughout the day, extracting maximum power from PV modules requires efficient MPPT algorithms.

Traditional MPPT techniques include:

- Perturb and Observe (P&O)
- Incremental Conductance (INC)
- Constant Voltage Method

Recently developed intelligent MPPT approaches include:

- Fuzzy Logic Controller (FLC)
- Artificial Neural Networks (ANN)
- Particle Swarm Optimization (PSO)
- Grey Wolf Optimizer (GWO)
- Deep Reinforcement Learning

These intelligent algorithms achieve faster convergence with lower oscillations around the maximum power point.

Power Electronic Converters

Power converters are responsible for efficient energy conversion between PV arrays, battery storage, utility grids, and EV batteries.

Recent converter technologies include

- High-frequency DC–DC converters
- Bidirectional Buck–Boost converters
- Three-level NPC inverters
- Modular Multilevel Converters (MMC)
- Silicon Carbide (SiC)-based converters
- Gallium Nitride (GaN)-based converters

Compared with conventional silicon devices, SiC and GaN converters provide

- Higher efficiency (>98%)
- Reduced switching losses
- Smaller heat sinks
- Higher switching frequency
- Compact system size

Battery Energy Storage System (BESS)

Battery storage has become one of the most important components of modern charging stations.

Its functions include

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- Solar energy storage
- Peak shaving
- Load leveling
- Voltage stabilization
- Backup during grid outage
- Renewable energy smoothing

Table 1. Common Battery Technologies Include

Battery Type	Advantages	Limitations
Lithium-ion	High efficiency	High cost
Lithium Iron Phosphate (LiFePO4)	High safety	Lower energy density
Solid-state battery	High energy density	Expensive
Flow battery	Long cycle life	Large installation space

III. OPTIMIZATION APPROACHES FOR GRID-CONNECTED SOLAR ELECTRIC VEHICLE CHARGING SYSTEMS

The increasing penetration of electric vehicles (EVs) and renewable energy resources has made the optimization of grid-connected solar EV charging systems a significant research area. The stochastic behavior of solar photovoltaic (PV) generation, fluctuating charging demand, varying electricity prices, battery degradation, and grid operational constraints create a complex multi-objective optimization problem. Consequently, optimization techniques are employed to maximize renewable energy utilization, minimize charging costs, reduce energy losses, improve battery lifetime, and enhance grid stability. An effective optimization framework enables intelligent energy scheduling by balancing the power supplied from photovoltaic arrays, battery energy storage systems (BESS), and the utility grid while satisfying the charging requirements of electric vehicles. Over the past decade, optimization methodologies have evolved from conventional mathematical programming to advanced artificial intelligence-based approaches capable of handling nonlinear and dynamic operating environments.

Conventional mathematical optimization techniques have long been utilized in energy management systems because of their deterministic nature and computational efficiency. Linear Programming (LP) remains one of the simplest optimization methods for

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minimizing charging costs and allocating energy resources under linear constraints. It provides globally optimal solutions for convex optimization problems and requires relatively low computational effort. However, practical EV charging systems exhibit nonlinear characteristics due to battery dynamics, converter behavior, and renewable energy intermittency, limiting the applicability of LP. To overcome these limitations, Mixed Integer Linear Programming (MILP) has been extensively adopted because it incorporates binary and integer decision variables representing charging schedules, battery switching operations, and grid interactions. MILP provides highly accurate scheduling solutions but experiences increased computational complexity as the number of vehicles and charging stations grows.

Dynamic Programming (DP) has also been widely applied in optimal battery management and sequential decision-making problems. By decomposing complex optimization tasks into multiple subproblems, DP effectively determines optimal charging strategies while considering battery state-of-charge, renewable generation, and electricity tariffs. Nevertheless, DP suffers from the well-known "curse of dimensionality," making it computationally expensive for large-scale charging infrastructures. More recently, Model Predictive Control (MPC) has become one of the preferred optimization frameworks for real-time charging management. MPC predicts future system behavior using mathematical models and continuously updates control actions based on forecasted solar irradiance, electricity prices, and charging demand. Although MPC demonstrates excellent dynamic performance and effectively handles multiple constraints simultaneously, its implementation requires accurate prediction models and considerable computational resources.

Because grid-connected solar EV charging systems involve highly nonlinear and multi-objective optimization problems, metaheuristic algorithms have gained remarkable popularity in recent years. These optimization techniques imitate natural biological processes and evolutionary behaviors to search for near-optimal solutions without requiring gradient information. Among these methods, the Genetic Algorithm (GA) has been extensively applied for charging scheduling, photovoltaic sizing, battery capacity optimization, and operational cost minimization. Inspired by Darwin's theory of natural selection, GA performs iterative optimization through selection, crossover, and mutation operations. Although GA provides robust global search capability and effectively handles nonlinear optimization problems, it often requires many generations to converge and may experience premature convergence depending on parameter selection.

Particle Swarm Optimization (PSO) has become another widely adopted optimization algorithm because of its simplicity and fast convergence characteristics. Inspired by the coordinated movement of bird flocks, PSO updates candidate solutions according to individual and collective learning experiences. Numerous researchers have applied PSO for maximum power point tracking (MPPT), charging scheduling, battery energy management, and converter parameter optimization. Compared with GA, PSO generally converges more rapidly while requiring fewer control parameters. However, the algorithm may become trapped in local optima when solving highly complex optimization problems involving multiple conflicting objectives.

Several nature-inspired optimization techniques have demonstrated superior performance in recent literature. The Grey Wolf Optimizer (GWO), developed based on the social hierarchy and hunting behavior of grey wolves, exhibits excellent exploration and exploitation capabilities while maintaining computational simplicity. GWO has been successfully employed in battery parameter estimation, MPPT control, charging optimization, and renewable energy management. Similarly, the Whale Optimization Algorithm (WOA), inspired by the bubble-net hunting strategy of humpback whales, has shown remarkable effectiveness in nonlinear optimization problems involving photovoltaic systems and electric vehicle charging stations. WOA provides a balanced trade-off between global exploration and local exploitation, resulting in improved convergence speed and solution quality compared with many conventional optimization methods.

Recent years have also witnessed the emergence of several advanced swarm intelligence algorithms with enhanced optimization capabilities. The Salp Swarm Algorithm (SSA), which models the chain movement of marine salps, has demonstrated high convergence accuracy and computational efficiency in renewable energy optimization. Likewise, the Harris Hawks Optimization (HHO) algorithm mimics the cooperative hunting strategy of Harris hawks and has proven effective in solving high-dimensional optimization problems associated with photovoltaic parameter estimation, charging scheduling, and battery sizing. Another promising approach is the Sparrow Search Algorithm (SSA), inspired by the foraging behavior of sparrows. Owing to its excellent population diversity and rapid convergence characteristics, SSA has recently gained considerable attention for smart charging applications and hybrid renewable energy management systems.

Artificial intelligence has revolutionized optimization methodologies for grid-connected solar EV charging infrastructure. Artificial Neural Networks (ANNs) are capable of learning complex nonlinear relationships among meteorological conditions, charging demand, battery characteristics, and grid operation. Consequently, ANNs have been widely employed for solar irradiance prediction, charging load forecasting, battery health estimation, and intelligent decision-making. Fuzzy Logic Controllers (FLCs) have also become popular because they effectively handle uncertainty and imprecise information without requiring detailed mathematical models. Fuzzy inference systems are extensively utilized in MPPT algorithms, battery charging control, converter switching, and energy management systems, particularly under varying environmental conditions.

Machine learning algorithms further enhance optimization by enabling intelligent forecasting and adaptive decision-making. Supervised learning techniques such as Support Vector Machines (SVM), Random Forests, Decision Trees, and Extreme Gradient Boosting (XGBoost) have demonstrated high prediction accuracy for charging demand, electricity prices, and renewable energy generation. More recently, deep learning architectures including Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), and Transformer models have substantially improved forecasting performance. Their ability to extract temporal and spatial features from large datasets allows more accurate prediction of photovoltaic power generation, battery degradation, and electric vehicle charging demand, thereby improving overall energy management.

IV. COMPARISON OF OPTIMIZATION METHODS

The increasing complexity of grid-connected solar electric vehicle (EV) charging systems has motivated researchers to investigate numerous optimization techniques to enhance system efficiency, reduce operational costs, improve renewable energy utilization, and maintain grid stability. Each optimization method exhibits distinct characteristics regarding computational complexity, convergence speed, scalability, robustness, and suitability for different charging scenarios. Consequently, selecting an appropriate optimization algorithm depends on the operational objectives, system size, uncertainty associated with renewable energy generation, and computational resources available for real-time implementation. A comprehensive comparison of these optimization methods provides valuable insights into their practical applicability and research potential.

Classical optimization techniques such as Linear Programming (LP), Mixed Integer Linear Programming (MILP), Dynamic Programming (DP), and Model Predictive Control (MPC) have been extensively employed during the initial development of smart charging systems. These methods provide deterministic solutions with high mathematical accuracy and are particularly effective when system models can be represented using linear or convex formulations. Among these techniques, LP demonstrates the lowest computational complexity and provides globally optimal solutions within a relatively short execution time. However, its inability to accurately model nonlinear battery dynamics and renewable energy uncertainty limits its application in modern charging infrastructures. MILP extends the capability of LP by introducing binary decision variables, making it suitable for charging scheduling and energy dispatch problems. Nevertheless, MILP becomes computationally intensive as the number of charging stations and connected electric vehicles increases, thereby restricting its scalability.

Dynamic Programming provides excellent performance in sequential optimization problems involving battery charging and energy management. Since the charging decision at each stage depends on previous system states, DP effectively determines optimal charging trajectories while considering future operating conditions. Despite its accuracy, the exponential growth of computational requirements with increasing state variables significantly limits its application in large-scale charging systems. Model Predictive Control has recently become one of the most attractive optimization techniques because it continuously predicts future system behavior using dynamic models and updates charging decisions accordingly. MPC effectively handles multiple operational constraints, renewable energy variability, and fluctuating electricity prices. However, its dependence on accurate forecasting models and relatively high computational burden remains a significant implementation challenge.

The limitations of deterministic optimization methods have encouraged widespread adoption of metaheuristic optimization algorithms. These algorithms perform global optimization without requiring gradient information and demonstrate superior capability for solving nonlinear, multi-objective optimization problems. Among these approaches, the Genetic Algorithm (GA) remains one of the most frequently adopted optimization methods because of its

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robustness and flexibility. GA efficiently explores large search spaces through evolutionary operators including selection, crossover, and mutation. Although GA consistently produces high-quality solutions, its relatively slow convergence rate and sensitivity to parameter tuning may increase computational time for large optimization problems.

Particle Swarm Optimization (PSO) has become one of the most popular optimization techniques due to its simple implementation and rapid convergence characteristics. The algorithm updates candidate solutions according to individual and global learning experiences, allowing efficient exploration of complex search spaces. Numerous studies have demonstrated that PSO achieves lower computational time than GA while maintaining comparable optimization accuracy. However, PSO occasionally experiences premature convergence, particularly when solving highly nonlinear optimization problems with multiple local optima. Various adaptive and hybrid PSO variants have therefore been proposed to overcome these limitations.

Among recently developed swarm intelligence algorithms, the Grey Wolf Optimizer (GWO) has demonstrated remarkable performance for renewable energy optimization. Inspired by the hierarchical hunting strategy of grey wolves, GWO maintains an effective balance between exploration and exploitation throughout the optimization process. Comparative studies indicate that GWO often converges faster than both GA and PSO while producing more stable solutions for photovoltaic parameter estimation and charging scheduling. Similarly, the Whale Optimization Algorithm (WOA) has shown competitive performance due to its effective search mechanism based on the bubble-net hunting behavior of humpback whales. WOA exhibits strong global optimization capability and efficiently avoids premature convergence, making it suitable for parameter optimization in complex charging systems.

Recent optimization research has increasingly focused on advanced swarm intelligence techniques such as Harris Hawks Optimization (HHO), Salp Swarm Algorithm (SSA), Sparrow Search Algorithm (SSAp), Artificial Bee Colony (ABC), Firefly Algorithm (FA), and Marine Predators Algorithm (MPA). These algorithms demonstrate superior optimization accuracy compared with earlier metaheuristic methods because they incorporate adaptive exploration mechanisms capable of maintaining population diversity throughout the optimization process. Comparative investigations have shown that HHO and Sparrow Search Algorithm generally provide faster convergence and improved solution quality than PSO and GA,

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particularly when optimizing renewable energy allocation and battery management strategies.

Artificial intelligence has introduced a new paradigm for optimization by enabling charging systems to learn optimal operating policies directly from historical data. Artificial Neural Networks (ANNs) provide accurate prediction of photovoltaic power generation, charging demand, electricity prices, and battery degradation, thereby improving optimization performance. Unlike conventional optimization algorithms, ANN-based methods continuously improve prediction accuracy as additional operational data become available. Similarly, machine learning algorithms such as Support Vector Machines (SVM), Random Forests, Decision Trees, and Extreme Gradient Boosting (XGBoost) have demonstrated high forecasting accuracy while maintaining moderate computational complexity. Their ability to model nonlinear relationships significantly enhances decision-making under uncertain operating conditions.

Deep learning techniques have further improved optimization accuracy by extracting complex temporal and spatial features from large datasets. Long Short-Term Memory (LSTM) networks have become particularly effective for photovoltaic power forecasting and charging demand prediction because of their capability to capture long-term temporal dependencies. Convolutional Neural Networks (CNNs), Gated Recurrent Units (GRUs), and Transformer-based architectures have also demonstrated remarkable performance in renewable energy forecasting and battery health estimation. These deep learning models significantly improve optimization outcomes by providing highly accurate predictions of future system conditions.

Table 2. Comparative Analysis of Optimization Methods for Grid-Connected Solar EV Charging Systems

Method	**Strengths**	**Limitations**	**Typical Applications**
Linear Programming (LP)	Fast, deterministic, globally optimal for linear problems	Cannot effectively model nonlinear systems	Energy scheduling, economic dispatch
Mixed Integer Linear Programming (MILP)	High scheduling accuracy, handles discrete variables	High computational complexity	Smart charging, unit commitment

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Dynamic Programming (DP)	Optimal sequential decision-making	Curse of dimensionality	Battery energy management
Model Predictive Control (MPC)	Real-time optimization, constraint handling	Requires accurate forecasting models	Smart grid energy management
Genetic Algorithm (GA)	Robust global optimization	Slow convergence, parameter sensitivity	Charging scheduling, PV sizing
Particle Swarm Optimization (PSO)	Simple implementation, rapid convergence	May converge to local optima	MPPT, charging optimization
Grey Wolf Optimizer (GWO)	Balanced exploration and exploitation	Moderate parameter tuning	Renewable energy management
Whale Optimization Algorithm (WOA)	High optimization accuracy	Computational cost for large populations	Converter tuning, energy scheduling
Harris Hawks Optimization (HHO)	Fast convergence, strong local search	Relatively new, limited industrial deployment	PV parameter estimation
Sparrow Search Algorithm (SSA)	Excellent convergence, high robustness	Limited long-term validation	Smart charging optimization
Artificial Neural Network (ANN)	Learns nonlinear relationships	Requires training data	Load and PV forecasting
Deep Reinforcement Learning (DRL)	Adaptive real-time optimization	High training complexity	Autonomous charging management
Hybrid AI–Metaheuristic Methods	Superior accuracy and robustness	Increased implementation complexity	Integrated energy management

V. RESULTS AND DISCUSSION

The comprehensive review of recent studies on grid-connected solar electric vehicle (EV) charging systems demonstrates that substantial progress has been achieved in the development of intelligent, efficient, and sustainable charging infrastructures. The integration of photovoltaic (PV) generation, battery energy storage systems (BESS), advanced power electronic converters, and artificial intelligence (AI)-based energy management has significantly improved the technical, economic, and environmental performance of EV charging stations. Research published between 2020 and 2026 indicates a clear shift from conventional charging systems toward smart, adaptive, and grid-interactive charging architectures capable of supporting large-scale EV adoption while maintaining grid stability and maximizing renewable energy utilization.

One of the most significant findings from the reviewed literature is the increasing effectiveness of solar photovoltaic integration in reducing dependence on conventional grid electricity. Earlier charging stations relied almost entirely on utility grids, resulting in high operational costs and increased peak demand. However, modern grid-connected solar charging stations utilize locally generated renewable energy to satisfy a considerable portion of charging requirements. Several studies have reported that integrating solar PV systems can substantially reduce grid energy consumption and operating expenses, particularly in regions with high solar irradiance. The inclusion of battery energy storage systems further improves renewable energy utilization by storing surplus solar energy during periods of high generation and supplying electricity during peak charging demand or low solar availability. This coordinated operation enhances charging reliability while minimizing fluctuations in grid power demand.

Another important observation is the rapid advancement of power electronic technologies. The widespread adoption of silicon carbide (SiC) and gallium nitride (GaN) semiconductor devices has significantly improved converter efficiency, reduced switching losses, and increased power density. Compared with conventional silicon-based converters, wide-bandgap semiconductor devices enable higher switching frequencies, smaller passive components, reduced cooling requirements, and improved overall charging efficiency. These improvements contribute to faster charging speeds and lower system operating costs while increasing the reliability of charging infrastructure.

The review also reveals considerable progress in intelligent energy management systems. Conventional rule-based controllers are gradually being replaced by predictive and adaptive energy management strategies capable of responding dynamically to variations in solar generation, charging demand, electricity prices, and battery state-

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of-charge. Artificial intelligence techniques have become central to this transformation by enabling charging systems to forecast future operating conditions and optimize charging schedules accordingly. Machine learning algorithms have demonstrated excellent performance in predicting charging demand, photovoltaic power generation, and electricity market prices, thereby improving the effectiveness of charging decisions. Deep learning models, particularly Long Short-Term Memory (LSTM) networks and Transformer architectures, have consistently achieved higher forecasting accuracy than traditional statistical approaches, making them highly suitable for intelligent charging applications.

Optimization algorithms represent another area where remarkable progress has been observed. Classical optimization techniques, including Linear Programming (LP), Mixed Integer Linear Programming (MILP), Dynamic Programming (DP), and Model Predictive Control (MPC), continue to provide reliable solutions for relatively structured optimization problems. These methods offer high mathematical accuracy and deterministic convergence but often struggle with the nonlinear and stochastic characteristics of modern charging systems. Consequently, metaheuristic optimization algorithms have gained increasing attention because of their ability to solve complex multi-objective optimization problems without requiring gradient information. Algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Harris Hawks Optimization (HHO), and Sparrow Search Algorithm (SSA) have demonstrated superior flexibility and robustness in optimizing charging schedules, renewable energy allocation, battery management, and converter control.

VI. CONCLUSION AND FUTURE SCOPE

The rapid growth of electric vehicle (EV) adoption has created an urgent need for efficient, intelligent, and sustainable charging infrastructure capable of supporting future transportation systems while minimizing environmental impacts. Grid-connected solar electric vehicle charging systems have emerged as one of the most promising solutions by integrating renewable energy generation with advanced energy management technologies. This review comprehensively examined recent advances in grid-connected solar EV charging systems, focusing on system architectures, photovoltaic integration, battery energy storage, bidirectional charging technologies, optimization approaches, and emerging intelligent energy management techniques. The analysis demonstrates that integrating solar photovoltaic systems with utility grids not only reduces dependence on

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fossil-fuel-based electricity but also improves energy security, decreases greenhouse gas emissions, and enhances the overall sustainability of electric mobility.

The review indicates that significant technological progress has been achieved in photovoltaic conversion systems, power electronic converters, battery management systems, and charging infrastructure during the last few years. High-efficiency photovoltaic modules combined with advanced maximum power point tracking (MPPT) algorithms have considerably improved renewable energy harvesting under varying environmental conditions. Similarly, the adoption of wide-bandgap semiconductor devices such as silicon carbide (SiC) and gallium nitride (GaN) has enhanced converter efficiency, reduced switching losses, and enabled compact charging station designs with higher power density. These technological developments have substantially increased the operational efficiency and reliability of modern charging stations.

Another important outcome of this review is the growing importance of battery energy storage systems (BESS) in renewable-powered charging infrastructure. Battery storage effectively mitigates the intermittent nature of solar energy by storing surplus photovoltaic generation during periods of high irradiance and supplying electricity during peak charging demand or low solar generation. Consequently, battery energy storage improves renewable energy utilization, reduces grid dependency, enhances voltage regulation, and increases charging reliability. However, battery degradation, high installation costs, thermal management, and recycling remain important challenges requiring continuous research and technological innovation.

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