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COMPREHENSIVE REVIEW OF EV CHARGING OPTIMIZATION

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ABSTRACT— The widespread adoption of electric vehicles (EVs) is revolutionizing the transportation industry while putting tremendous pressure on current energy infrastructures. With EV charging behaviors becoming more dynamic and sophisticated, smart and scalable solutions are needed to maintain grid stability and energy efficiency. This paper provides an in-depth overview of state-of-the-art EV charging optimization methods with a focus on artificial intelligence (AI) and machine learning (ML) methods. We suggest a classification model that separates optimization techniques into scheduling-based and energy management-based categories, covering a broad spectrum of algorithms ranging from heuristic models to deep reinforcement learning and real-time predictive analytics. These AI-based methods improve load forecasting, minimize energy expenses using dynamic pricing, stabilize demand and supply, and enable integration with renewable energy sources like solar and wind. Emerging technologies such as vehicle-to-grid (V2G), IoT-enabled infrastructure, and edge computing also facilitate real-time, adaptive decision-making for smart charging systems. Our results indicate the increasing promise of AI-based optimization in creating a sustainable, efficient, and resilient EV ecosystem that aligns with global energy transition objectives.The application of digital twins and simulation platforms enables better testing of EV-grid interactions before mass deployment. AI also enables user behavior and location-based personalized charging strategies, which enhance user satisfaction.

Keywords— EV charging, Optimization, Artificial Intelligence, Machine Learning, Smart Grid, Reinforcement Learning, Scheduling, Load Forecasting, Energy Management, Deep Learning.

1. INTRODUCTION

Growing worldwide demand for sustainability, carbon zero, and clean energy has created an unprecedented wave of the adoption of electric vehicles (EVs). As predicted, there could be hundreds of millions of EVs on the roads in the next several decades, and therefore, the need for efficient and scalable EV charging infrastructure has become a first-order priority.

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Charging point operators, utilities, and city planners are getting under mounting pressure with the demand for charging, grid stability, and lowering energy bills, particularly during peak usage. Unlike traditional vehicles, EVs are connected directly to the grid, and hence their charging behavior is now a part of the overall energy system. This is compounded by the dynamic nature of user response, fluctuating electricity prices, station capacity constraints, and the intermittent nature of renewable energy sources such as solar and wind. All these demand data-driven, adaptive solutions to make the charging infrastructure efficient, reliable, and sustainable. Artificial Intelligence (AI) and Machine Learning (ML) are now strong solutions to tackle such challenges. Utilizing historical data and current trends, AI algorithms are capable of predicting energy loads, scheduling charging for peak use, managing grid loads, and charging optimization for an individual or a fleet. Reinforcement learning, deep learning, and heuristic techniques have shown to be very promising in addressing the smart charging system complexity. The purpose of this paper is to deliver a comprehensive survey of AI- and ML-based EV charging optimization methods. We propose a taxonomy with two general groups into which research may fall: Scheduling-Based Optimization, aiming for optimal scheduling of charging sessions, and Energy Management-Based Optimization, aiming for power allocation and coordination on the grid in an efficient manner. Under an optimized framework, we review state-of-the-art algorithms, look into public datasets, and present a comparison of evaluation metrics to identify the strengths and weaknesses of current research.

2. LITERATURE SURVEY

The rising popularity of electric vehicles (EVs) has given rise to increased research aimed at maximizing EV charging using artificial intelligence (AI) and machine learning (ML) methods. The main objectives are to enhance scheduling efficiency, lower peak load on the electrical grid, facilitate smooth integration with renewable energy sources, and overall enhance the user experience. In the subsequent subsections, we emphasize significant contributions under major areas of smart scheduling, load forecasting, energy management, decentralized optimization, and infrastructure planning.

[1]A paper presented a novel deep reinforcement learning (DRL) framework to optimize large-scale urban EV fleet charging schedules. The model was trained in a dynamic pricing environment and demonstrated the ability to learn complex trade-offs between user convenience, grid stability, and charging cost. The DRL agent leveraged real-time feedback from the environment, adapting its strategy based on historical data, grid load, and pricing signals. This approach significantly improved both scheduling efficiency and demand distribution across different time slots.

[2]In another article, different machine learning models—namely, Random Forest, Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) neural networks—were compared in short-term EV load forecasting. Findings indicated that LSTM models performed better than conventional methods by capturing temporal and nonlinear relationships in charging patterns. By incorporating external features like weather, calendar

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events, and traffic information, the models indicated better prediction accuracy, which is essential for advance grid management and the prevention of overload.

[3]This research introduced a demand-side management approach that couples heuristic optimization techniques (e.g., Genetic Algorithm and Particle Swarm Optimization) with real-time pricing data for electricity. This hybrid scheduling algorithm sought to level the load curve by spreading charging workloads across off-peak hours and reducing energy expenditures for users and utility operators alike. Simulation outcomes revealed significant peak demand and operational cost savings for smart grid operators.

[4]This work investigated applying federated learning to construct privacy-protecting models for predicting EV loads and understanding users' behavior. Rather than centralizing personal user information, predictive models were jointly trained on geographically dispersed charging stations. The distributed structure not only guaranteed user confidentiality but also provided strength against data compromises and fast adaptation to local usage trends

[5]A research on integration of renewable energy proposed a hybrid AI architecture that blended weather prediction models with intelligent charge point management. The architecture employed predictive analytics to optimize EV charging based on solar and wind energy availability, shifting charging schedules dynamically to times of excess generation. This resulted in improved grid stability, more consumption of clean energy, and less dependence on electricity generated from fossil fuels.

[6]Another study suggested a digital twin-driven real-time monitoring and optimization of EV charging infrastructure. The digital twin was a virtual representation of the actual grid ecosystem, regularly refreshed with real-time information from IoT sensors. The system provided predictive maintenance, fault detection, and simulation of diverse charging scenarios, thus enhancing reliability, system uptime, and operational planning.

[7]This paper discussed the use of edge computing in EV infrastructure, where distributed computation and control were conducted locally at edge nodes. By mitigating cloud decision-making demand, the system kept latency low and enhanced the responsiveness to rapid load changes. Integrated with IoT devices at charging points, edge computing supported quick, autonomous decisions for load balancing, fault management, and dynamic pricing.

[8]Last but not least, a case study in the Netherlands utilized geospatial and behavioral data to maximize the location of public charging points. Through insights on traffic pattern trends, trip lengths, and past charging history, the study created a data-enabled strategy for metropolitan energy grid planning. The framework considered regional energy need, accessibility, and user population, leading to more balanced and effective infrastructure deployment.

3. METHODOLOGY

To efficiently manage the increasing demand for charging electric vehicles (EVs) and its effects on the power grid, a number of optimization strategies have been proposed. These methods are intended to schedule the charging in such a manner as to balance grid stability, economic optimality, and customer satisfaction. A multitude of techniques have been developed, each appropriate to varying problem complexities, goals, and operational

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restrictions. In this paper, we classify and discuss the most significant methods utilized for EV charging scheduling. The categories of optimization techniques covered are explained in the following subsections.

1. Mathematical Optimization Techniques

Mathematical optimization techniques try to develop the EV charging schedule problem into a tractable mathematical model. Methods such as Linear Programming (LP), Nonlinear Programming (NLP), Quadratic Programming (QP), Mixed-Integer Programming (MIP), and Dynamic Programming (DP) are most common. These models find the optimal charge schedules subject to clearly defined constraints like grid capacity, cost of energy, and vehicle specifications. They are computationally effective for small- to medium-sized systems with linear or mildly non-linear dynamics. They are, though, disappointing in terms of scalability and real-time responsiveness in complicated environments.

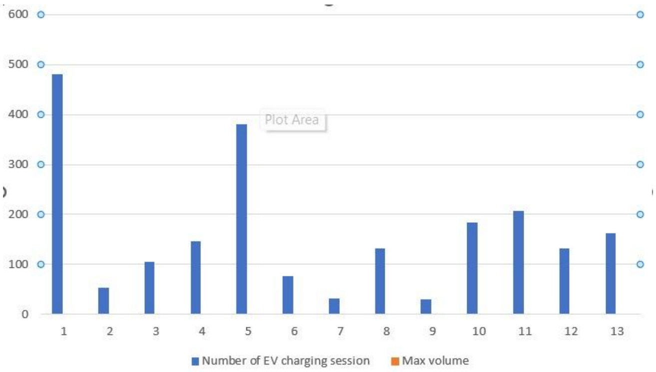

Fig-3.1:Max Volume produced per session

2. Metaheuristic Algorithms

Metaheuristic algorithms are nature-inspired methods employed to tackle intricate, high-dimensional, and non-convex optimization tasks in EV scheduling. They are more generalized into Single-Solution Based (e.g., Simulated Annealing, Tabu Search) and Population-Based (e.g., Genetic Algorithm, PSO, ACO) categories. They traverse various candidate solutions iteratively to find near-optimal solutions. They are specifically beneficial in multi-objective optimization where traditional approaches are inadequate. Even though they do not promise a global optimum, their adaptability and versatility make them appropriate for practical, large-scale EV Networks.

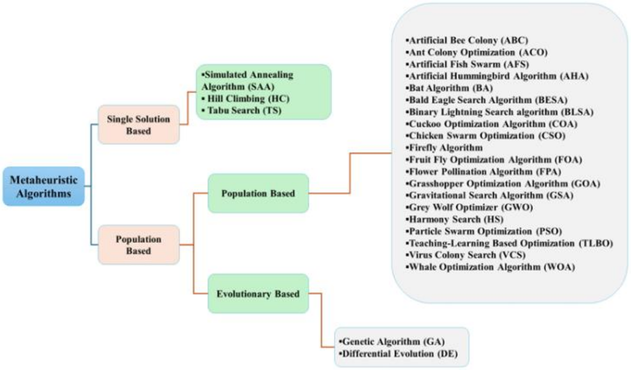

Fig-3.2:Classification of metaheuristics algorithms applied for EV charge scheduling.

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3. Machine Learning Techniques

Machine Learning (ML) allows predictive and adaptive EV charging behaviors based on historic and real-time data. Load forecasting is handled through supervised learning techniques such as SVM and Random Forest, and unsupervised methods such as K-means assist in planning infrastructure. Dynamic pricing and charging decisions in environments with uncertainty are supported by Reinforcement Learning (RL) and Deep Learning (DL) models such as LSTM and DRL. Patterns of user behavior and grid load, which ML models learn and upon which they operate to optimize schedules of charging, are the processes these techniques present. These methodologies provide real-time responsiveness and enhanced long-term efficiency in smart grids.

4. Scheduling Architecture Models

EV charging coordination architecture is important in affecting system performance. Centralized systems have all charging decisions made by a central entity in light of global data, making for tight control but scalability issues. Decentralized systems give each EV control over deciding its own schedule, and flexibility goes up but typically causes system-wide optimization to decrease. Hierarchical architectures merge the strengths of both and employ several layers of aggregators to oversee local decisions with some global control. Architecture selection affects latency, computational requirements, and communication demands in the charging network.

5. Stakeholder-Oriented Objective Modeling

Efficient charge scheduling has to take into account the heterogeneous objectives of stakeholders: grid operators, aggregators, and EV users. Grid operators seek to reduce voltage drops, energy losses, and infrastructure stress. Aggregators seek profit maximization, reduction in energy cost, and optimal use of resources. EV users value convenience, cost-effectiveness, battery longevity, and reaching a target State of Charge (SoC). Modeling these different objectives within optimisation algorithms ensures that charging strategies are balanced, fair, and system-friendly. Multi-objective structures are frequently applied to balance conflicting stakeholder demands

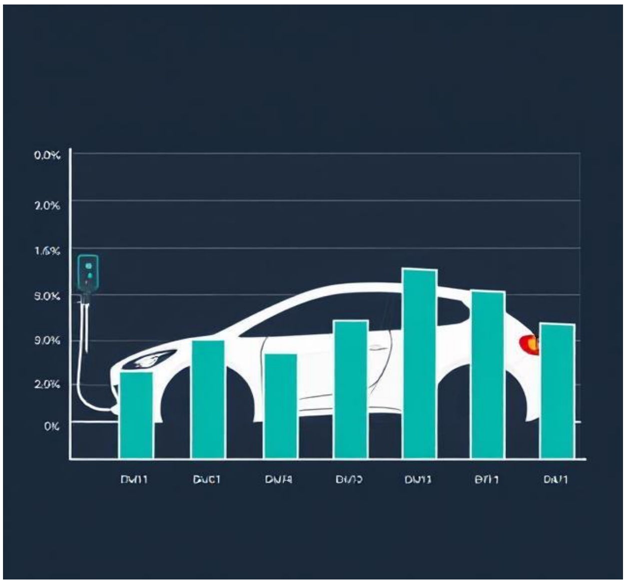

Fig-3.3:Stakeholder Value Trade-off Analysis

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4. Results

The research indicates that intelligent EV charge scheduling minimizes stress on the power grid due to random charging. Centralized systems are capable of controlling large numbers of EVs simultaneously, balancing grid load and charging demand effectively. Yet, they get complicated and more difficult to handle with increasing numbers of EVs. Decentralized systems, in contrast, provide greater control to users but might not always be optimal for the whole grid.

Hierarchical models leverage the advantages of centralized and decentralized systems. They apply layers of control—e.g., local and central aggregators—to better handle charging. These models scale well to large numbers of EVs and can easily respond to evolving grid conditions while safeguarding user privacy and minimizing processing time.

The review also underscores the success of various optimization approaches. Basic mathematics-based methods suit small systems, whereas Genetic Algorithm and Particle Swarm Optimization are capable of dealing with complex problems. Machine learning, particularly deep learning and reinforcement learning, holds considerable promise in terms of demand forecasting and optimizing real-time charging choices.

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