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Optimization Strategies for Electric Vehicle Charging and Routing: A Comprehensive Review

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Highlights

- The paper discusses overview of electric vehicle optimal scheduling techniques and need for the same.
- A comprehensive review about the methodologies for optimum scheduling of electric vehicles is made.
- The paper discusses various uncertainties associated with electric vehicle charging scheduling.
- Paper gives a comprehensive review about various algorithms and optimization techniques used.
- Paper summarizes the applications of different algorithms used for EV scheduling.

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Abstract

Based on information from recent research, by 2045, Electric Vehicles (EV) will dominate the roads with presence of more than 80% of its kind. Hence, these vehicles' grid level penetration will increase proportionally, which challenges the existing grid infrastructure in terms of its reliability and energy management capabilities. New techniques to store and consume massive quantities of energy from the power grid, as well as infusing the captive energy within the EV in response to grid demands, are emerging with the advent of electric vehicles. Everything could be handled smoothly only if we schedule the EV operation (charging/discharging) more optimally and efficiently using scheduling algorithms. Despite the existence of many routings and charging schedule computations, nature-inspired optimization approaches might play a critical role in responding to such routing challenges. Researchers have created several optimum scheduling approaches, such as Dynamic Programming, Differential Evolutionary Optimization Techniques, Collaborative Optimization Scheduling, Two-stage optimal scheduling strategy, and so on. The optimum schedule review examines the operation of an EV fleet while considering uncertainty sources and varied EV operating circumstances by integrating heuristic and meta-heuristic techniques. This paper exhibits a deep review on the various EV optimal scheduling techniques and adopted algorithms which are the emerging best practices like predictive analytics, dynamic routing, user centric planning, multi-objective optimization, etc. that reflect the industry's focus on leveraging advanced technologies, data-driven decision-making, and collaborative approaches to enhance the efficiency and sustainability of electric vehicle routing and charging scheduling.

1. INTRODUCTION

Owing to society's growing concern over environmental and energy issues as well as the dramatic advancements in battery in recent decades, there are new opportunities for the widespread adoption of electric vehicles (EVs). Figure 1 depicts how electric car development has changed. Since governments have established legislation to control the imbalance of the ecosystem, the use EV users have gained a lot of benefits [1]. Optimal charging strategies for EV aggregators are being explored to lower charging costs because concerns have arisen about poor coordination in charging requirements of EVs and their implications on the present-day grid's capacity to effectively serve the increasing demand in load [2]. The majority of EVs are idling during the daytime, but they could work with power grid to offer ancillary services when necessary. A Vehicle-to-Grid (V2G) architecture that would let utilities or aggregators control Electric Vehicles (EV) through grid-to-car communication was put forward in [3]. Peak shaving, power quality improvement, frequency regulation, spinning reserve, valley filling and support for

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renewable power are some of the auxiliary services offered by EVs [4]. Most research papers were written to address the difficulties in planning the use of EVs in parking areas (PLs), including fast charging capacity, varying electricity prices, the number of charging points, and charging limits [5]. However, only a few studies addressed advanced techniques for online booking, scheduling, and location locating [6,7]. If charging costs are not accounted for in the context of their connectivity and are assumed to follow an independent methodology unaffected by electricity, they may have an adverse effect on the stability of electricity network. A distributed pricing method for congestion management during EV charging is introduced in [8]. As mentioned in [9,10], an aggregator could be created to address these issues. When compared to traditional charging stations, battery-swapping stations (BSSs) have faster EV time slots [11].

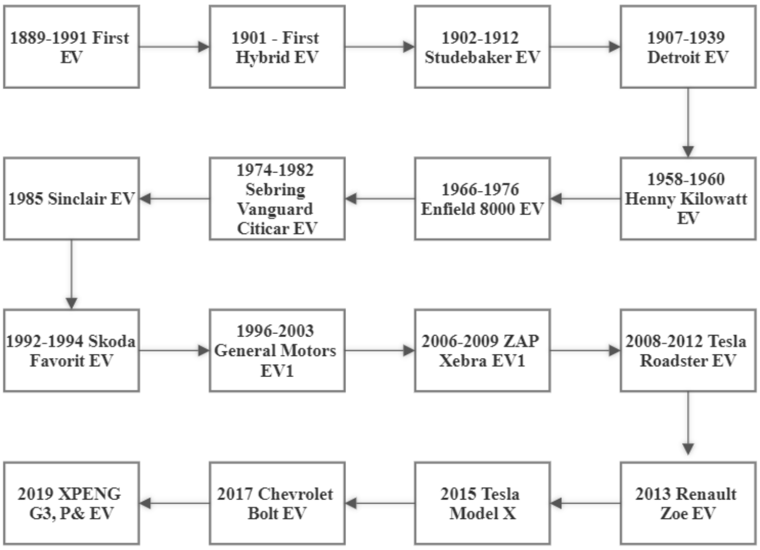

Figure 1. *Historical Progression of Electric Vehicle*

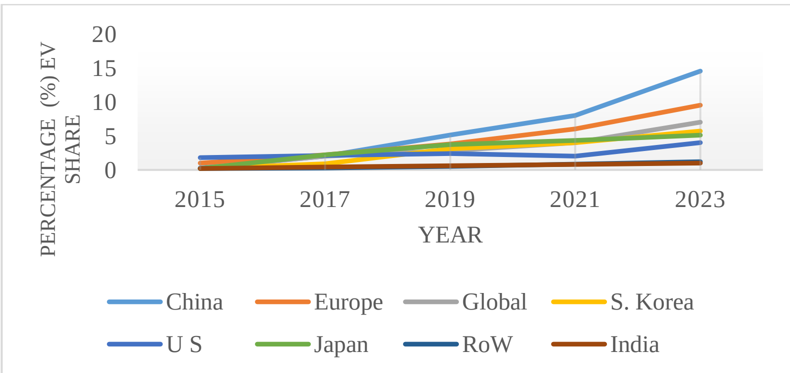

Figure 2. *Global short-term EV share of new passenger vehicle sale by region*

Few research has investigated electric vehicle routing problems (EVRPs) that account for both vehicle charge scheduling and routing. The issue of traffic jams has received a lot of attention. EVs are driven at different speeds and under varying driving conditions because of the presence of traffic. Time-dependent travel speeds as a solution with consideration of congestion tolls in EVRP with time windows (EVRPTW) is proposed in [12]. When a fault occurs, the safety of an EV's distribution system, the microgrid (MG) can disengage from it and operate independently, attempting to compensate for the grid's reliability Moreover, as mentioned in [13,14], the MG can boost acceptance of distributed generation (DG)into the existing grid while meeting local consumer power requirements. Figure 2 depicts the global market share of short-term electric vehicle new passenger vehicle sales by region. Positive trends are emerging around the world, implying that these EVs will eventually rely on the existing power grid for power exchange, necessitating optimal scheduling strategies. The diversity of EV charging behavioral traits, such as wait periods, time of start, and power demand are major challenges in managing the EV charging. In [15], the prediction of revised pattern-based sequential forecasting (PSF) was tried to compare to SRV, KNN and random forest

(RF) methodologies. Due to their inherent performance in during decision-making scenarios, reinforcement learning methods, as discussed in [16], have just recently become popular. They are better compared to optimization approaches because they do not make use of prior knowledge of accurate model, but they learn the very best behaviors. This paper's goal is to provide a thorough overview of the optimal scheduling for electric vehicles, including the optimal charge scheduling and route scheduling algorithms that are used in different optimization methods. Review papers that have already been published look at EV adoption factors, ideal service operation models, computational scheduling strategies, and EV outcomes. This review paper addresses the following objectives or research areas discussed in Table 1, which makes this paper attractive to the active researchers.

Table 1. *Details of objectives discussed in the paper*

Review Topics Covered	Objectives	Issues Adressed
Algorithm classification	Categorize and classify different types of optimal charging and routing algorithms	• Different optimal charging and routing algorithms categorized based on their underlying optimization techniques. • Distinguishing features of different algorithmic approaches
Factors considered in optimization	Identify the key factors and parameters considered in the optimization process	• Critical factors influencing the design and optimization of charging and routing algorithms. • How do these factors vary in different algorithmic approaches.
Integration of real-time data	Explore the incorporation of real-time data in optimal charging and routing algorithms	• Impact of integrating real-time data, such as traffic conditions, energy prices, and charging station availability on algorithm performance.
User-centric approach	Investigate the inclusion of user-centric elements in charging and routing algorithms	• Accountability of algorithms for user preferences, behaviors, and convenience. • Effectiveness of these algorithms.
Challenges and limitations	Identify and analyze the challenges and limitations associated with current charging and routing algorithms	• Common challenges faced by existing algorithms in real-world implementations. • Limitations adressed in algorithms.
Scalability and Generalizability	Examine the scalability and generalizability of optimal charging and routing algorithms	• Performance of algorithm under different scenarios. • Challenges and considerations arise when scaling these algorithms for broader applications.

The rest of the paper is organized as: section 2 discusses an overview of electric vehicle scheduling. Optimal scheduling methodologies for EVs are reviewed in section 3, Uncertainties in the EV charging scheduling are discussed in section 4. Comparison of performances with various algorithms is discussed in section 5, summary of this paper is discussed in section 6. The conclusions and future works are detailed in section 7 and 8, respectively.

2. AN OVERVIEW OF ELECTRIC VEHICLE SCHEDULING

This section provides an overview of different optimum routing, charge scheduling approaches, algorithms, and mathematical models utilized by researchers. Figure 3 illustrates a high-level overview of EV charge scheduling approaches based on pricing, an optimization approach, and goals. In response to rising environmental concerns, the transportation sector is experiencing a dramatic shift. Governments, EV firms, and energy companies have pushed for the growth of electric cars (EVs). The interaction of an electricity system and a transport network is determined by charging pricing and transportation scheduling, both of which are modeled by a marginal cost coordination optimization formulation discussed in [17].

Furthermore, the EV aggregators' optimal scheduling problem is modeled in [18] with consideration of EV owner satisfaction by considering V2G operational cost, the appropriate charging electricity price, and delivering the vehicle with the batteries fully charged, presents a significant challenge in developing an efficient pricing model that allows for adequate power extraction from the grid. To address this issue, an electric vehicle charging costing mechanism is designed such that it benefits both end-users and energy retailers. A distributed cost model for EV load management during charging was presented in [19] to address similar issues. A complete and accurate optimization model that considers all crucial elements of an EV sharing service schedule, such as time-varying charging price, multi-task and multi-temporal operation, and service quality. The optimization model allows for judgment across various time intervals and considers time-of-use (TOU) energy cost information in the energy framework. For achieving robust timetabling of EV, it is essential to model the ambiguity of the upstream electricity cost. To solve this problem, a robust optimal scheduling of EV aggregators is proposed [20].

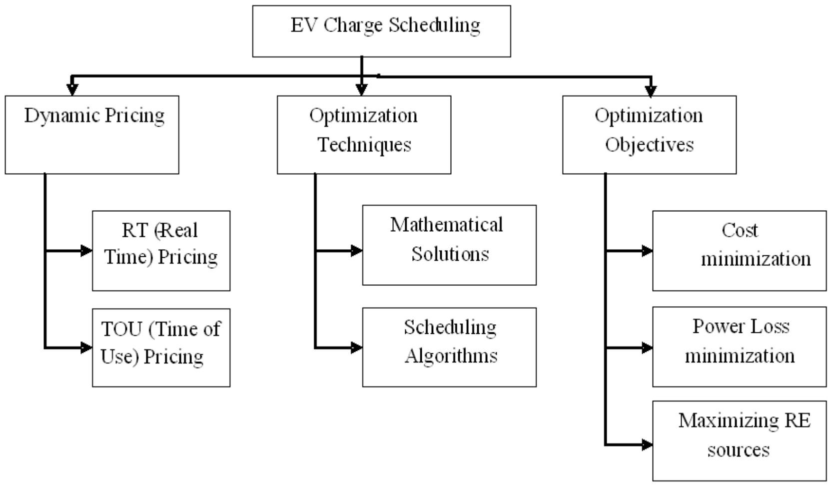

Figure 3. *Overview of EV charge scheduling approaches*

The investigation of optimal microgrid dispatching focuses primarily on the generation forecasting of DE resources in a microgrid and energy management in a single MG. A review of scheduling methods for an MG assisted distribution system was proposed, which optimizes the distribution network's economic benefits but does not consider the effect on the MG side. Figure 4 shows the order of EV charging schedules referred to in [21]. Generally, the overall modeling of EVs is considered, and the energy flow direction inside the EV is less restricted; however, since few years, research on electric vehicle charging stations has primarily focused on the traditional AC slow charging method, with charging infrastructure mostly situated in suburban complexes and densely populated areas cannot meet the expectation of fully centralized charging station to support energy services to users very fast. DC fast charging method, takes very little time for full charging, has provided a new hope for EV popularization and revenue generation through public EV services (taxis and public transportation systems), as discussed in [22,23]. The pervasive use of EVs, on the other hand, may increase both electricity consumption and peak power load. A stochastic modeling and simulation of an EV fleet operation was discussed in [24], with the objective of deepening cooperation among both smart grids and EVs by handling the charging/discharging of individual connected EVs. This is achieved by ignoring any impending and significant increase in the power load, which could result in a visible conflict of interest. In the scenario of large EV integration, uncoordinated operation may deteriorate power network operations, likely to result in transformer overloading or dissatisfied power quality. As a result, large-scale EV real-time charging optimization (RTCO) should be considered, because individual EV charging behavior, conventional load profiles, renewable generation output, and real-time price (RTP) are highly stochastic, which is typically a resource scheduling approach with multivariable epistemic uncertainties [25,26]. Table 2 shows the review of the study on electric vehicle access to the distribution network.

Table 2. *A review of the study on electric vehicle access to the power distribution grid*

Reference	Identified Research	Details of the Research Study
[27-29]	Access to the distribution network for electric vehicles through multi-objective optimization	The optimization function is to maximise voltage reliability while minimising operational costs.
		Firefly optimization techniques proposed to solve the complexity in EV scheduling after establishing a distribution grid scheduling model that into account demand side management.
		Relative study was done on the operational cost of the distribution grid dissatisfying value of EVs users.
[30-32]	The distribution network's vulnerability to the effects of EV discharge behaviour	Develop a distributed generation (DG) corresponding technique based on EV charge/discharge behaviour.
		Examine how electric vehicle access affects power quality in distribution networks.
		Investigate the effects of electric charging, as well as the method of treatment and network access model. Analyse the impact of various electric vehicle capacities on distribution network load, network loss, and voltage.
[33]	Evaluate the reliability of the distribution network incorporating electric vehicles	The effect of EV penetration, charging/discharging limit, EV battery capacity and reliability of EVs are investigated.
[34-36]	New technologies and Strategies	Proposed a feedback methodology for a realistic case in a typical urban setting.
		suggest a distributed structure for vehicle grid integration that takes connectivity and physical networks into account.
		Suggest a discharging and charging strategy, as well as multiple load management programmes, to manage the economic and technical EV penetrations.

A joint model wherein EVs and thermal power plants are collectively timetabled was investigated in [37], with all scheduling methodologies split into two stages. The initial stage consists of scheduling electric vehicles for the day ahead to develop an EV charging/discharging load guidance curve that satisfies the scheduling requirement. Given the ambiguity of electric vehicles, charging/discharging plans appropriate for user requirements can be reformulated in the second stage in response to variations in independent user requirements, improving users' satisfaction with the scheduling algorithm, most researchers are concentrating their efforts on predicting EV charging/discharging and optimizing distribution network resources. EV load predictive modeling based upon Monte Carlo method (MCM), beginning with the transportation sequence of EVs and various charging/discharging methods was proposed in [38]. The MCM is used for the operation of EVs to engage with random events and uncertainty and accurate forecasting results are obtained. The responsibility for charging EVs can be delegated to the operator. It is worth noting that the EVSEs must be used efficiently to reduce the charging period and thus the cost. To address these issues, the scheme proposed in [39] optimizes the charging pattern to reduce cost of charging and time, and model predictive control (MPC) has been utilized in a variety of other areas in recent years, including electrical network control, optimized scheduling, and power flow management to cope with demand and supply uncertainties along with system constraints. To address this, the electric bus departure plan, route scheme, and electric volume of battery swapping are ascertained by the electric bus's speed of driving, which is estimated by the road traffic model is shown. The traffic flow model algorithm was then used to create the BSS model. The configuration of a control scheme for the concurrent powertrain topology of PHEVs was dealt in [40]. The scheme of control is intended to reduce fuel usage and multiple gear shift occurrences over a broad driving period while preserving the EV battery condition within permissible limits. In this control strategy, a dynamic rule-based controller was used with a comparable consumption minimization strategy (ECMS). A dynamic battery framework (based on empirical data) that portrays the impacts of different crucial stress factors has been put in place as a key goal in [41] to minimize cycle deterioration by evaluating numerous optimal EV charging schedule scenarios in tandem with the analytical hierarchy process (AHP). A day ahead comprehensive cost-minimizing optimal scheduling methodology for charging EVs in a stochastic atmosphere while maintaining local network constraints and EV owner satisfaction was presented in [42]. An aggregator in a wholesale energy market is expected to optimize schedules and day-ahead routines for effective communication.

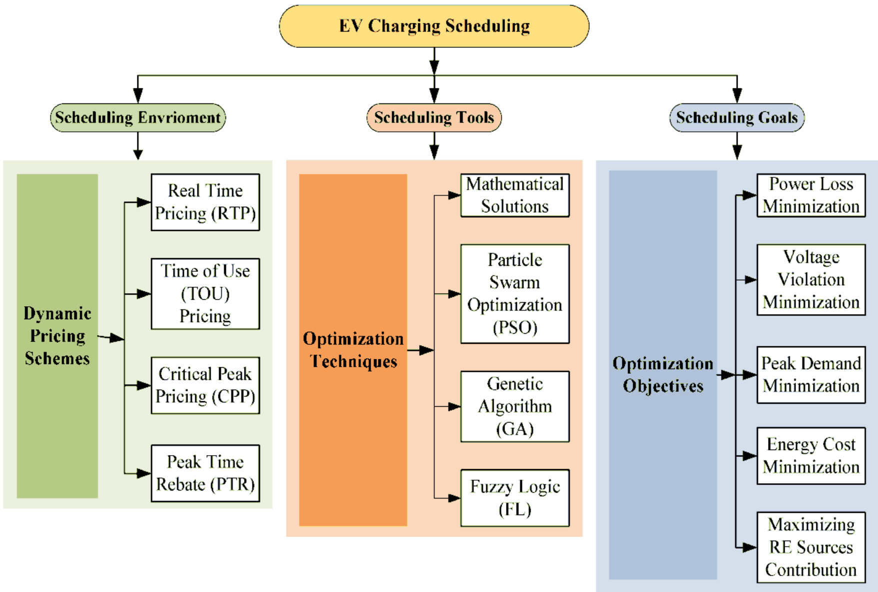

Figure 4. *Classification of domestic EV charging scheduling*

A dynamic programming-based algorithm for optimizing thermal comfort as well as efficiency was discussed in [43]. When the effectiveness of the algorithms used to predict EV user behavior was examined, it was discovered that the error variances were typically large. This is because EV charging trends differ greatly and thus, there is no single algorithm. Classification of various charging patterns as well as the application of machine learning (ML) algorithms to detect charging behavior in each categorization was discussed in [44]. A comparative analysis of the strengths and weaknesses of electric vehicle (EV) scheduling algorithms is shown below Table 3.

Table 3. *Comparative analysis of the strengths and weaknesses of electric vehicle (EV) scheduling algorithms*

Scheduling Approaches	Strength	Weakness
Energy Efficiency	All scheduling algorithms excel in optimizing energy efficiency by leveraging off-peak hours or renewable energy availability	No specific weakness in this category, as energy efficiency is a common focus
Range Optimization	Scheduling algorithms effectively minimize the risk of running out of battery power by optimizing charging schedules.	Limited predictive accuracy may result in suboptimal range optimization in certain scenarios.
User Convenience	All scheduling algorithms enhance user convenience by minimizing waiting times and providing accurate predictions.	User adherence issues may impact the ability to fully realize the benefits of user convenience.
Adaptability to Real-Time Data	Scheduling algorithms excel in adapting to real-time data, adjusting to dynamic situation	Computational complexity might limit the real-time applicability of certain algorithms
Computational Complexity	Some algorithms manage computational complexity well, ensuring real-time applicability.	Others may struggle with computational demands, limiting their usability in dynamic situations.

Limited Predictive Accuracy	Certain algorithms improve predictive accuracy by integrating advanced analytics and machine learning	However, accuracy challenges still exist, impacting the overall effectiveness of predictions.
Dependency on Infrastructure	Algorithms consider infrastructure availability, ensuring effective scheduling based on charging station locations.	Limited charging infrastructure may still pose challenges, affecting algorithm effectiveness.
User Adherence	Some algorithms address user adherence issues by incorporating user-centric design principles.	However, user behavior remains a significant source of uncertainty
Scalability Issues	Some algorithms effectively address scalability issues, ensuring applicability in large-scale networks.	Others may struggle with scalability, limiting adoption in densely populated EV environments.
Charging Station Congestion	Certain algorithms consider the potential for congestion, enhancing user experiences.	However, in scenarios with high demand, congestion issues may still arise.

In general, all scheduling algorithms share strengths in improving energy efficiency, optimizing range, and enhancing user convenience to some degree. However, challenges such as limited predictive accuracy, user adherence issues, and computational complexity are shared by multiple algorithms. The effectiveness of algorithms can differ in areas like grid integration, adaptability to real-time data, and scalability, making them suitable for specific use cases. Ultimately, the choice of an EV scheduling algorithm depends on the specific goals, priorities, and constraints of the application environment. Advances in research and technology aim to address weaknesses and enhance the overall performance and applicability of these algorithms. There have been vast developments during these days in adopting various methodologies for the electric vehicle scheduling. A few among them are discussed below:

- Integration of Machine Learning: Recent advancements involve incorporating machine learning techniques to improve the predictive capabilities of scheduling algorithms. Machine learning models can analyze historical data, user behaviors, and external factors to enhance the accuracy of predictions related to energy prices, traffic conditions, and charging station availability.
- Reinforcement Learning Approaches: Researchers are exploring the application of reinforcement learning in EV scheduling. Reinforcement learning algorithms enable EVs to learn and adapt their charging strategies based on environmental conditions, user preferences, and system feedback, leading to more dynamic and adaptive scheduling.
- User-Centric Design: Advances in user-centric design focus on tailoring scheduling algorithms to user preferences and behaviors. Incorporating user feedback and considering individual preferences in the scheduling process can improve user satisfaction and adherence to optimal charging plans.
- Fleet Management Optimization: There's a growing emphasis on optimizing EV scheduling within fleet management scenarios. This involves coordinating the charging schedules of multiple vehicles to maximize fleet efficiency, reduce operational costs, and ensure that all vehicles are adequately charged when needed.
- Distributed Energy Resources (DER) Integration: Recent trends involve integrating EV scheduling with distributed energy resources, such as solar panels and stationary energy storage. This holistic approach aims to optimize energy usage, storage, and distribution within the broader context of smart grids and renewable energy sources.
- Multi-Objective Optimization: Researchers are exploring multi-objective optimization techniques to consider multiple conflicting objectives simultaneously, such as minimizing charging costs, reducing environmental impact, and optimizing user convenience. These approaches aim to find a balance among different objectives for a more comprehensive solution.
- Block chain Technology: The integration of block chain technology is gaining attention for secure and transparent transactions within the EV ecosystem. Block chain can be used to facilitate peer-to-peer energy trading, enable secure transactions at charging stations, and provide a decentralized approach to managing EV charging schedules.

- Real-Time Data Integration: Continued advancements involve enhancing the real-time capabilities of scheduling algorithms. Integrating real-time data on traffic conditions, energy prices, and grid status allows for more dynamic and responsive charging plans, improving overall system efficiency.
- Edge Computing for Decentralized Processing: Some recent trends focus on leveraging edge computing for decentralized processing of data. Edge computing can reduce latency and enhance the real-time capabilities of scheduling algorithms, allowing for faster decision-making at the edge of the network.
- Open Standards and Interoperability: Efforts are being made to establish open standards and interoperability in the EV charging infrastructure. Standardization facilitates communication and data exchange between different components, enabling a more seamless integration of EV scheduling methodologies across diverse platforms and networks.

These trends indicate a broader shift toward more intelligent, adaptive, and user-friendly EV scheduling methodologies, driven by advancements in data analytics, machine learning, and the integration of emerging technologies. As technology continues to evolve, it's likely that additional innovations will further enhance the capabilities and efficiency of electric vehicle scheduling methodologies.

3. REVIEW ON OPTIMAL SCHEDULING METHODOLOGIES FOR ELECTRIC VEHICLES

This section describes the various optimal scheduling methodologies for electric vehicles. In order to aid the decision-making process easy for the aggregator, the smart grid model considers renewable energy generators, electricity spot prices, the local market, demand response, and wholesale market for electric vehicles, and the newly proposed optimization algorithm. Using this algorithm, the total operating cost was reduced by 72%. This viable reduction percentage is computed by multiplying the arbitrary solution by the suboptimal solution [45]. To avoid producing inaccurate results, some uncertainties, such as load with generation, ESSs, demand response (DR), EV consumer, loads with DR, generation, electricity markets, and so on, should be considered when modeling smart grids. Table 4 shows the presence of these uncertainty factors in optimal scheduling problems and Figure 5 demonstrates how relative the uncertainty sources within the optimal allocation problems are. A new time-variable EV route-scheduling problem with traffic management. To solve the model, a mixed-integer linear programming (MILP) supported within adaptive large neighborhood search heuristic is developed. Using benchmark instances, the framework and approach were validated and evaluated thoroughly. The ALNS heuristic provides significantly better results to the situation in less time than the traditional optimization software.

Table 4. *Presence of uncertainty factors in optimal scheduling problems*

Reference	Demand Response Used	Utilization of EV Energy	ESS Connected	EV-Consumers Involved	BSS Used	Uncertainty Sources Connected
[46]	No	No	No	Yes	Yes	Yes
[47]	Yes	Yes	Yes	Yes	No	Yes
[48]	Yes	No	No	No	No	Yes
[49]	Yes	Yes	No	No	Yes	Yes
[50]	No	Yes	Yes	No	No	No
[51]	No	Yes	No	No	Yes	Yes
[52]	No	Yes	No	Yes	Yes	Yes
[53]	No	Yes	No	Yes	Yes	Yes

A collaborative optimization scheduling strategy for distribution infrastructure and a multi-microgrid can fully exploit the DE in the MG to solve the optimal scheduling problem created by the region's multi-microgrid and distribution network coordination. Furthermore, this method will help to enhance the power quality of the electric grid contributing to economic advantages for the MG. The degree of satisfaction of EV owners is also considered, and a two-layer model hierarchical coordination method is used to coordinate multi-microgrid and distribution networks. The optimal objective function of each layer was determined based on the power supply and load predictions. The efficacy of the two-layer model is validated and the benefits of this approach in multi-microgrid models and power distribution system stability are demonstrated. A stochastic gap decision theory (GDT) approach for EV aggregators can be used to model uncertainties like departure/arrival times and initial SOC, considering the market rate variations in the day-ahead electricity market. The objective function is to maximize the aggregator's capital gain under market price uncertainty. A microgrid (MG) optimum operation, which considers the swapping storage integrated station (CSSIS) of EV with battery fast-charging station (BCS) concept is framed with the basics of queuing theory and is realized based on the fast-charging users' behavioral patterns where deterministic approach for predicting and modeling an EV fleet to create reliable charging/discharging profiles can be used to manage the EV fleet, a genetic algorithm (GA)-based single-objective optimization was used. The envisaged optimization gives the effective trade-off among G2V and V2G operation costs to maximize the benefits of EV batteries by coordinating charging/discharging during variable pricing periods.

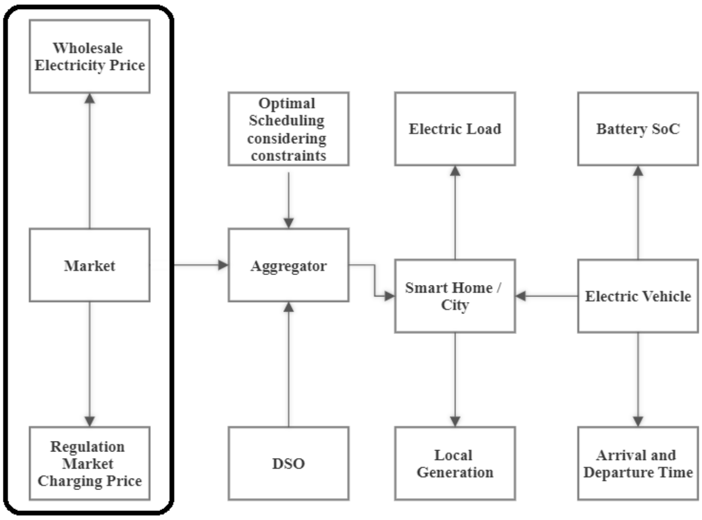

Figure 5. *Relationship of uncertainty sources within the optimal allocation problems*

Charging in real time optimization (RTCO) of sizable EVs, as multifaceted stochastic resource distribution problem is investigated in [54]. Multi-dimensional approximate dynamic programming (ADP-RTCO) is used to make subsequent optimal decisions when dealing with the complex RTCO of EV fleets. The ADP-hierarchy RTCOs have two levels. The RTCO of the EV fleets framed as a multidimensional energy storage system in the top level by batching EVs into various virtual clusters. The value function is then approximated with the help learning-based policy iteration methodology, in which a priority-based re-allocation algorithm is used to generate accurate charge power for EVs. ADP-RTCO was developed to maximize flexibility and reliability in vague environments through online learning. ADP-RTCO is optimal and sturdy in terms of both cost-saving and load-flattening concerns, according to extensive simulation results. Figure 6 depicts the multiple objectives of EV charge scheduling. Since the EVs are well related to the utility grid via the charging station, the scheduling objectives include the most important constants regarding the EV charging infrastructure [55]. A double-stage scheduling policy for sizable EVs to ameliorate the detrimental effects of decentralized charging is discussed in [56]. EV travel survey data are used to approximate the uncontrolled charging requirements of independent EVs and their agglomeration. In stage one, EVs and thermal power plants are set to run simultaneously. The charging/discharging load curves of EVs, as well as the optimal outcome strategies of the thermal power plants, were designed to lower overall operating expenses and the standard deviation of the entire load profile for each time frame of the day. In stage two, the EV load management and controllers utilize rolling optimization to create specific charging/discharging strategies for customers based on the guiding load profile. It is presumed that lowering the price of vehicle discharge compensation will enhance consumers’ willingness to engage in scheduling as well as customer satisfaction. To eliminate the "dimension disaster" due centrally controlled deployment of massive quantities of EVs, the K-means clustering algorithm is being used to group the EVs into different batches. The particle swarm optimization (PSO) algorithm can then be employed to solve the model, with each group scheduled as a unit.

Joint scheduling of BESS activity and non-dispatchable EV charging load (with the same deadline) in the presence of RE generation, electricity prices, and EV arrivals driven by the capability of using used EV batteries as BESS at charging stations was investigated in [57]. They also developed an interactive program that addresses the cost-cutting scheduling issue of an EV charging station operator. When the number of EVs is large, the constructed interactive program cannot be solved exactly by brute-force methods owing to computational complexity. Jiang in [58] investigated the scheduling of EV charging in public areas, especially those near worksites that serve fixed users. This study aimed to optimize EV charging in parking areas by incorporating an ESS and a PV system. A cost-minimization problem was used to define the charging optimization problem. A grey wolf optimizer (GWO) is then developed as a strategy for finding an optimized solution, considering the condition of the constraints of the optimization problem, an intelligent binary grey wolf optimizer (IBGWO) is suggested to strengthen the optimization and convergence rate accuracy. Eventually, a real-time EV charging scheduling scheme based on short-term PV power prognostication and IBGWO is proposed. To appraise the effectiveness of the suggested strategy, several cases were designed for the simulation. While emulating the solution for the suggested charging scheduling framework, the experimental experiments demonstrated that the proposed IBGWO outperforms other meta-heuristic algorithms. In addition, the suggested method can increase PV energy utilization while decreasing operator electricity prices.

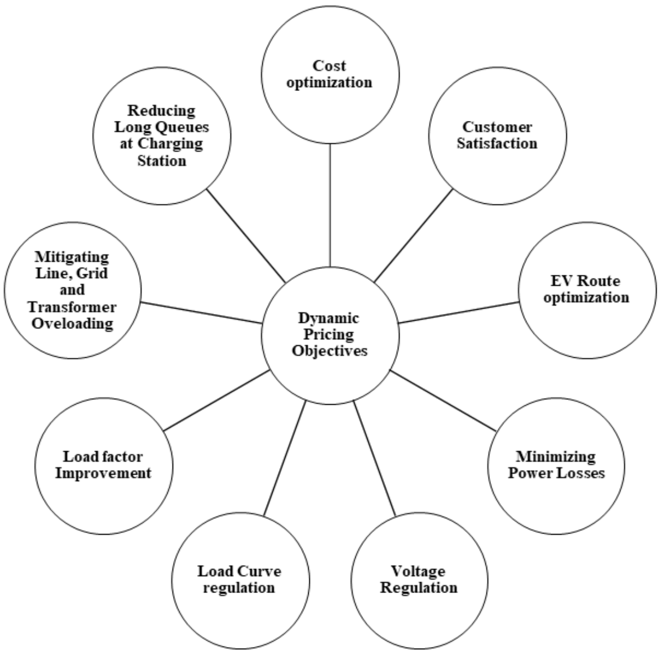

Figure 6. *Multiple objectives of EV charging scheduling*

A new model in which EVs replacing ICE vehicles could be a solution to the particulate matter (PM) 2.5 pollution problem is investigated in [59]. Uncontrolled charging of EVs, on the other hand, would pose a challenge to the power system's operation. As a result, some control over the EV charging is required, particularly in residential networks. The GA was used to resolve the optimization problem and the simulation results exemplify a reduction in the transformer peak load, loss of energy arbitrage benefit, power loss, and transformer life. Shereef proposed an integrated control at the service provider level in [60], which optimally performs peak clipping with EVs. The framework uses a charging station (CS), an aggregator, a control center, and EVs. Taking an IEEE 14 bus system as reference, the peak demand is optimally allocated to perform peak clipping among the aggregator and utility. The results indicate that it is optimal for peak demand scheduling. The results improve when EVs are dispersed into two separate buses instead of a single bus. As a result, a different optimal routing and charging method is discussed. Overall, the goal of pursuing the optimal scheduling technique is to lower the EV owner's total cost while increasing profit. This can be accomplished by employing one of several scheduling algorithms, all of which are described in the following section. A control methodology for a PHEV with configuration of parallel powertrains was developed in [61]. The control strategy is intended to reduce fuel consumption and multiple gearshift events over a broad range of driving times while preserving the battery SOC within an acceptable limit. A controlled straight-back concept of the PHEV power train was employed as the design basis. In this case, the ECMS employs both transmission gear ratio and engine torque as dependent variables, obviating the need to develop a separate gearshift scheme and increase the power train's effectiveness. The entire control strategy is intended for use in a variety of operating regimes. Computational modeling is used to substantiate the approach against the optimal benchmark obtained via dynamic programming-based optimization, and the outcomes are used to fine-tune controller parameters. The work proposes a rigorous and relatively close RB+ECMS control scheme for concurrent PHEVs functioning in CS/CD or blended modes, which incorporates the logic of gear shift scheduling inside this energy management system, an algorithm with gear shift delay (GSD) aimed at eliminating continuous gear shifts and thus enhancing driving experience and driving dynamics, and a SOC control system that includes a feed-flux control system. The ideology of the multi objective techno economic environmental approach is suggested for coordinating EV charging and discharging in [62]. For the first time, end-user energy prices, battery deterioration, grid interplay, and CO2 emissions were designed and simultaneously optimized in the frame of reference of a home microgrid while supplying frequency regulation [63]. Compared to unregulated EV charging, the proposed technique saves 88.2 percent on energy prices, 67 percent on battery deterioration, 34 percent on CO2 emissions, and 90 percent on grid interplay, and to accomplish a 41.8 percent improved performance in grid usage with numerous optimum solutions, the grid operators must recompense the end energy user and EV user for their expensed revenue loss of 27.34 percent and 9.7 percent, respectively, in order to increase their involvement in energy services.

Voltage profiles are likely to worsen owing to the significant growth in EV numbers, resulting in distribution system overloading. Controlling the SoC of EVs in a coordinated manner could provide an impactful solution to minimize the issues and may delay communication infrastructure reinforcement. To lessen computational effort, sequential power flow estimation is used, which encapsulates a wide range of uncertainties associated with EV mobility behavior and attitude, such as stochastic daily trip ranges and arrival and departure times [64]. The results obtained from a test network shed light on the effect of unpredictability and the inability to deal with risk factors during optimization. Planning with a more liberal initial EV battery charge level improves the steadiness and operational feasibility of optimized schedules. A topological deep reinforcement learning (DRL) technique for coordinating the energy usage of distributed energy resources (DERs) such as ESS and EV in a smart home context is proposed in [65]. In contrast to the Q-learning algorithm, which is framed on a distinct action space, the suggested technique schedules the energy usage of household DERs and appliances in a continuous state space based on the improved result from the consumer operational environmental condition. A computational study was conducted in domestic air conditioners, washers, rooftop solar photovoltaic systems, energy storage systems, and EV charging with time of use (ToU) pricing. The proposed DRL supported HEMS algorithm optimizes the day-ahead planning of home appliances under varying climatic conditions and EV driving patterns with hourly scheduling settlement. The use of multi-stage probability programming in a smart home system to cut the price of energy acquisition for an average home is discussed in [66]. In this case, the usable electric vehicle (EV) vehicle-to-home (V2H) capability is combined with an energy storage system (BSS) controlled by an energy management control system. Being one of the major contributors, a suitable analytical model for battery ageing cost is also considered in problem statement. As a result, numerous strategies, such as with or without deterioration cost, BESS, and poorly coordinated charging are explored at different charging rates. The problem’s sensitivity to various EV and BESS charging rates was also explored in [67]. Moreover, the effect of potential battery storage expense future savings on the residential energy management system is being researched. Finally, the Value of the Stochastic Solution (VSS) metric is being used to evaluate the stochastic optimization method's effectiveness.

An EV scheduling algorithm that incorporates fuzzy logic system (FLC) in a charging infrastructure to significantly boost charging characteristics is proposed in [68]. The FLC assists the EV charting algorithm in logically determining an appropriate pair of CSs and EVs. The algorithm is designed to eliminate EV congestion by lowering the charging wait time and stabilizing the charge request rate. The maximum weight and random scheduling algorithms were considered [69], and the proposed scheduling algorithm came up with improving the efficiency of the EVCS in terms of wait period and tariff. Mavrovouniotis solved the problem of scheduling using ant colony optimization (ACO) for large number of EVs at a single station in such a way that the overall latency of the problem is kept to a minimum in [70]. Because of the charging station's physical and power limitations, namely the maximum contractual power and consumed power disparity among the electric feeder's lines, generating a suitable and efficient schedule is a tricky problem to coordinate. From the experimental outcomes, using ACO is very effective and outperforms the other methodologies. Based on whale optimization algorithm (WOA), the improved whale optimization algorithm (IWOA) adds a Gaussian mutation operator, crowding degree factor, and differential evolution operator to the framework [71]. The results of nine fine examples demonstrate that the IWOA greatly improves the accuracy and computational speed of the WOA. Researchers even use IWOA to model and find a solution trying to locate EV charging stations under service risk limitations. The popularization of electric vehicles with limited battery capacity has raised the crucial problem of how to charge them efficiently and successfully [72]. The above problem, colloquially known as EVCS, has been demonstrated to be NP-hard. The majority of previous works simply frame the EVCS challenge as a subjective vehicle routing problem to be dealt with discrete optimization. To accommodate the mathematical model, researchers created a mixed-variable differential evolution (MVDE) algorithm for the suggested EVCS system. The results demonstrate improved efficiency of the proposed framework for both synthesized and real-world networks. The advancement of PEVs continues to accelerate, and utilities and PEV users must consider how to effectively integrate large-scale PEVs with an electric grid [73]. This article suggests a distributed method of control with a consensus mechanism for large-scale PEV charging coordination, with an emphasis on grid-side preference. The proposed coordination strategy has two objectives: reducing charging power losses and increasing the available PEV energy for V2G facilities. To achieve these objectives, incremental cost operations were created [74]. Simulation outputs efficient charging coordination with limited communication to reduce the charging energy loss and support the V2G facility. Huang [75] suggested a charging-scheduling scheme for hybrid electric vehicle charging contexts. Apart from conventional charging scheduling algorithms, which only consider G2V and V2G instances, this algorithm considers emerging mobile charging vehicles (MCV), such as G2V, MCV2V, and V2V. Furthermore, because it is based on consortium block chains, the suggested optimized charging scheduling framework guarantees the privacy and security of the power system, and is built on a dual-objective optimization framework that aims to maximize user satisfaction while minimizing user costs, while considering various metrics such as charging/discharging entity location, time spent waiting, and EV steering speed, among others. An enhanced non-dominated sorting genetic algorithm (NSGA) is proposed to solve this, and the results indicate that the NSGA algorithm outperforms the V2V-and G2V-based algorithms. Unregulated electric vehicle charging behaviors may cause load perturbations and other active impacts as the number of cars increases [76]. To manage EV charging burden in the power grid, an electric vehicle charging and discharging strategy (EVCDS) based on a charging decision function (CDF) and a discharging decision function (DDF) is proposed. The CDF and DDF will engage with the battery's remaining energy, the EV charging routines, and the charging effectiveness of the station. To ascertain whether to discharge, charge, or do nothing, all sub-functions are evaluated and merged into the DDF and CDF. In the numerical results, researchers created a situation for private and commercial vehicles. EVCDS outperforms other strategies in decreasing the charging price fluctuations and improving the distribution of stations' charging requirements. Charging an EV takes more time than refueling a fossil-fueled vehicle [77]. Charging stations must be scheduled in advance based on the journey of the demander EVs for effective resource scheduling. Such frequent charging and scheduling may potentially expose user information, such as whereabouts, driving patterns, schedules, and so on. In these cases, EV matching is usually performed centrally, exposing private information to third party matching parties using Biochromatic Mutual Nearest Neighbor (BMNN) tasks [78]. The BMNN simulation not only does the proposed matching algorithm provide an acceptable assignment for all stakeholders, but it achieves effective matching in complex situations where new suppliers and demanders appear and some departments; furthermore, owing to the sheer character of its design, it offers an effective validation process for changing environments than the conventional steady search algorithm, reducing the overall user wait period before matching. EVRPs have emerged as a recent research emphasis with the advancement of EV technology [79]. The goal of this study is to find a low-cost approach that includes finding an optimal location and number of BSSs, as well as an optimal route planning built on stochastic customer needs for an EV battery swap station (BSS). Furthermore, the traditional recourse strategy and precautionary stockpiling policy are expanded to account for the effects of both batteries and vehicles simultaneously. Following this, the Pareto optimality concept can be incorporated in the EVRP to accelerate the choice of BSS patterns. Many cities across the world have designed and implemented an integrated system of EVCS and BESS to significantly enhance the utilization of PV energy to establish efficient and sustainable cities [80]. This article suggests a grid-connected PV battery energy storage (PBES) EVCS optimization model for sizing BESS and PV as well as determining BESS charging/discharging patterns. Various optimal scheduling algorithms were discussed above to solve the optimal EV scheduling problem. Several algorithms are available to solve the scheduling problem, including GA, ACO, MAPSO, EVCS, HVNS, EVCDS, and ADMM, which are discussed in detail [81,82]. Table 5 below shows specific examples or case studies illustrating the impact of uncertainties on scheduling and cost. These studies illustrate how uncertainties, whether in energy prices, traffic conditions, charging station availability, or user behavior, can impact the effectiveness of EV scheduling algorithms and result in cost implications. Addressing these uncertainties is crucial for developing more robust and adaptive scheduling methodologies in the evolving landscape of electric vehicle operations.

Table 5. *Specific examples or case studies illustrating the impact of uncertainties on scheduling and cost*

Scenario	Case Study	Uncertainty	Impact on Scheduling	Impact on Cost
Energy Price Variability	Studies in found that while scheduling algorithms considering price fluctuations were effective in normal conditions, unexpected peak prices led to increased charging costs, highlighting the need for improved price prediction models.	Fluctuations in electricity prices due to market dynamics and demand patterns.	EV charging schedules optimized for lower-cost periods may become less effective during unexpected spikes in electricity prices.	Users or fleet operators may experience higher charging costs during periods of unforeseen price volatility.
Traffic Conditions	Studies in found that scheduling algorithms, while effective in normal traffic scenarios, faced challenges in adapting to unexpected congestion, leading to deviations from the optimal plans and potential cost implications.	Unforeseen traffic congestion and delays during a scheduled EV trip.	Scheduled charging stops may be missed or delayed due to unexpected traffic, impacting overall travel time and charging plan adherence.	Delays in reaching charging stations may result in additional costs or penalties for missing scheduled charging windows.
Charging Station Availability	Findings in [99] revealed that unexpected station closures or high demand periods could lead to suboptimal charging plans, affecting both travel time and costs.	Sudden changes in charging station availability due to maintenance, malfunctions, or unexpected closures.	EVs relying on scheduled charging at specific stations may face challenges if the stations become unavailable.	Detours to alternative charging stations may incur additional travel time and costs.
User Behaviour Variability	The user-centric scheduling approaches discussed in were effective in normal conditions, unexpected deviations and uncertainties that affected both travel time and costs.	Variability in user behaviors, such as unplanned route changes or deviations from plans.	Algorithms may struggle to predict and adapt to unexpected user behavior, leading to suboptimal charging plans.	Users deviating from optimal plans may experience higher costs g or missed incentives.

4. UNCERTAINTIES IN THE OPTIMIZATION OF EV CHARGING CONTROL

The optimization of electric vehicle (EV) charging control involves addressing various uncertainties arising from dynamic and stochastic factors. These uncertainties can significantly impact the effectiveness of charging control strategies. Here are some key uncertainties in the optimization of EV charging control discussed in Table 6.

Table 6. *Key uncertainties in the optimization of EV charging control*

Uncertainty	Remarks	Impact
Energy price fluctuation	Cost varied depending upon demand, time and market conditions	Affect cost-effective charging station economics
Traffic condition	Subject to accidents, road closure, unexpected congestion	Influence travel times and questions feasibility of optimal routing plans
Charging station availability	Availability depends on maintenance, malfunctions, or unexpected closures	Deviations from the planned charging schedule, causing inconvenience.
Renewable energy generation	Overall electricity generation is variable and depends on weather conditions	Uncertainty in the carbon footprint and cost-effectiveness.
User behavious	Personal preferences, unforeseen events, or changes in travel plans	Impact the overall effectiveness of algorithms, leading to suboptimal results
Battery degradation	Charging patterns, temperature, and usage	Affect long-term planning and impact the overall lifespan of the EV battery
Predictive Models	Traffic prediction or energy price forecasting, is not perfect	Inaccurate predictions may lead to suboptimal charging plans, reducing the efficiency
Regulatory changes	Changes in government regulations, incentives, or policies	Affect the economic viability and attractiveness of certain charging strategies, influencing investment decisions

Addressing these uncertainties in the optimization of EV charging control requires robust and adaptive algorithms that can dynamically adjust to changing conditions. Strategies such as real-time data integration, machine learning for predictive modeling, and scenario-based planning can help mitigate the impact of uncertainties and enhance the resilience of EV charging optimization systems. Additionally, communication and coordination among various stakeholders, including energy providers, charging infrastructure operators, and EV users, are crucial for adapting to dynamic conditions and uncertainties in the charging environment. Problems with deterministic optimization presuppose that the data are precisely known in advance. Certain information (such as power requirements, electrical generation, EV charging/discharging durations, electricity costs), are known with absolute certainty for many real-world issues like EV charging. Despite the abundance of literary works on distributed EV charging control, none of it has considered these uncertain aspects. It is unlikely that algorithms will be implemented successfully in the real world if they do not adapt to these uncertain elements. Many of the algorithms for scheduling charges in the research treat electric vehicles (EVs) as static loads with predetermined spatiotemporal variables and do not account for their mobility. EV charge scheduling with consideration for mobility, on the other hand, can adjust to a variety of temporal changes, including erratic arrivals and departures as well as spatial patterns, such as charging locations, the accessibility of slots at CSs, their locations as well as the dynamic requirements. More particularly, an EV may plug in at any time during the day and may plug out prior to the set time limit. Due to these uncertainties, the initial charge schedule cannot be followed until the schedule horizon has passed. As shown in Figure 7, the uncertainties may arise from the mobility side, demand side, network side, energy generation side and the tariff side.

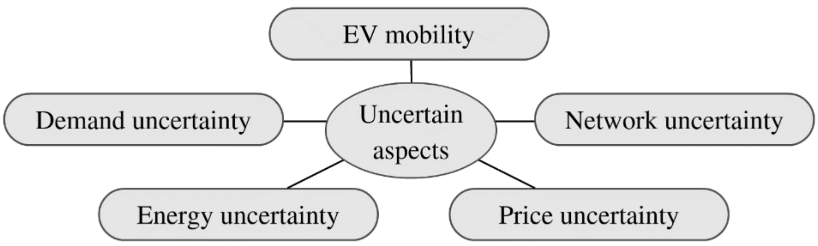

Figure 7. *Uncertainty aspects in EV charging*

Evaluating electric vehicle (EV) scheduling algorithms involves assessing their performance against various metrics or criteria to ensure their effectiveness in achieving desired objectives. The choice of metrics can depend on the specific goals of the scheduling algorithm and the priorities of stakeholders. Common metrics and criteria used to evaluate EV scheduling algorithms is shown in Table 7.

Table 7. *Common metric and criteria used to evaluate Electric Vehicle scheduling algorithm*

Criteria	Metric	Rationale
Charging Cost	Total cost associated with charging considering • Electricity prices • Demand charges • Penalties or incentives	To optimize economic efficiency
Energy efficiency	Energy consumed per unit/distance	Maximise energy efficiciency of EV operations ensuring optimal use of • Available battery capacity • Minimising environmental impact
Travel time	Time taken for completing trip	• Enhance the overall user experience • Improve the competitiveness of EVs
User convenience	Adherence to preferred charging times and locations	• Provide convenient and acceptable charging plans for users • Improving the likelihood of adherence
Grid impact	Grid stability • Load balancing • Renewable energy integration	Optimize charging to • Reduce peak loads • Support renewable energy integration • Contribute to a more resilient grid
Predictive accuracy	Accuracy of predictions related to • Energy prices • Traffic conditions, • Charging station availability	Algorithms need to demonstrate accurate forecasting to make informed decisions
Operational scalability	Performance of algorithm	Can effectively handle larger fleets and charging infrastructure
Robustness to uncertainties	Adapt to unforeseen events or changes in parameters	Handle uncertainties and dynamic conditions, ensuring reliability in real-world scenarios
Fairness and equity	Considers fairness and equity in charging access among different users or EVs	• Equitable distribution of charging resources • Avoiding disparities in charging opportunities
Adoption and user satisfaction	User satisfaction • Surveys • Adoption rates • Feedback	Success of scheduling algorithms depends on • User acceptance • Satisfaction • Willingness to adopt optimized charging plans
Environmental impact	Considering factors such as • Carbon emissions • Use of renewable energy sources	Minimize environmental impact contribute to sustainability goals

The selection of specific metrics depends on the context and goals of the EV scheduling algorithm. Also, a comprehensive evaluation may involve combining these metrics to provide a holistic assessment of algorithm performance.

5. PERFORMANCE COMPARISON OF VARIOUS EV SCHEDULING ALGORITHMS

The different approaches to optimal scheduling are compared and examined in detail in this section, as well as the various algorithms and mathematical models that are employed. Various methodologies were compared in that review based on the technology employed, benefits, and drawbacks. Table 8, details different methodologies used for the optimal scheduling of EVs which improved the computation efficiency and scalability, [83] designed with a smart microgrid model, [84] to reduced transmission power fluctuation, [85] which made operation cost trade-off thus improving convergence speed operation cost and waiting time. This also avoided the penalty, disaster problems, improved the voltage level and overcomes the congestion problem by minimizing the charging expense.

Table 8. *Methodologies for Optimal Scheduling of Electric Vehicle*

Technology Used	Advantages	Limitations
V2G Control Strategy	With EV participation, the cost of generation is reduced, and the voltage levels are improved.	Reactive power assistance for EV batteries is not considered.
Variable Neighborhood Search - Differential Evolutionary PSO (VNS-DEPSO)	Reduce operating costs of SMGs in uncertain environments.	The number of evaluations is restricted
Multi-Microgrid Collaborative Optimization Scheduling	During distribution network system operation, transmission power variations, node voltage variations and line network losses are lowered.	Does not consider economic optimization.
Charging–Swapping–Storage Integrated Station (CSSIS)	MG's total daily operating cost is being reduced.	The peak-to-valley difference expanded without considering optimal scheduling
Genetic Algorithm (GA) based Single objective optimal modeling	Find out the best trading among G2V and V2G operational expenses.	Additional power demand on the grid fluctuates erratically and dramatically.
Two-stage scheduling strategy	Avoids the dimensionality disaster problem	Total cost increases partially due to the existence of compensation costs
GSD - Gear Shift Delay algorithm	Attempting to avoid continuous gear changes and intensifying riding/driving experience	Increased fuel consumption
Augmented non-dominated ε-Constraint (ANEC) algorithm	Reduce battery degradation	Sustainability should be improved.
EV charging algorithm	Decreases the overall expense of charging the Electric vehicle pool.	The higher the operational cost required to mitigate the danger of inadequate charge
Genetic Algorithm (GA)	Reduce the price of peak demand, energy losses, and transformer ageing.	The EV owners' hedging advantage loss is being presented as a penalty cost.
Ant Colony Optimization (ACO) metaheuristic algorithm	Reduce the overall delays of the scheduling issue.	Variable charging rate is not considered
A multi-level distributed algorithm for supervised reinforced learning	Using the energy usage schedule, users can reduce their electricity costs.	The HEMS concern has become highly complicated.
The scenario generation algorithm	Legitimate accuracy and disregarding battery deterioration	This raises the overall cost to an intolerably good level.

Fuzzy logic control-based EV scheduling algorithm	Solve the EV congestion issue and reduce wait period	Poor charging request rate
Genetic Algorithm (GA)	Low peak demand, transformer loss of life and power loss costs.	The penalty price and the power loss price are the maximum in the scenario of dump charging.
Hybrid Variable Neighborhood Search (HVNS) algorithm	Improving the Logistics Distribution System by Incorporating Uncertain Data More Efficiently	More running time is required.
Mixed-Variable Differential Evolution (MVDE) algorithm	Reduce overall time expense, charging expenditure, and State of Charge gap of all Electric Vehicles.	MVDE should forego the last estimate in order to improve others.

Figure 8 compares the costs of various optimal scheduling methods, including ODS, IBGWO (improved binary grey wolf optimizer), SFL-TLBO (Shuffled Frog leap-teaching and learning-based optimization), OEVC (only utility of electric vehicle concerned) scheme, and MOTEEO (multi objective techno-economic environmental optimization). According to the graph, the total cost for the IBGWO scheduling algorithm is 52$, whereas the MOTEEO algorithm consumes only 17$. The SFL-TLBO method performed better with less computational effort for large-scale problems. They can increase their benefits by 81 percent by providing frequency control services to end-electricity consumers under MOTEEO.

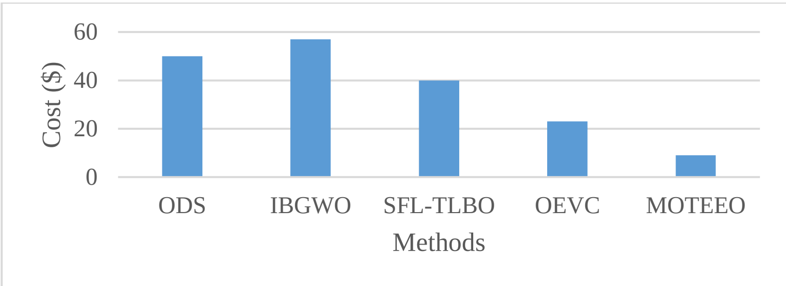

Figure 8. *Comparison of total operational cost for different optimal scheduling methods [86–88]*

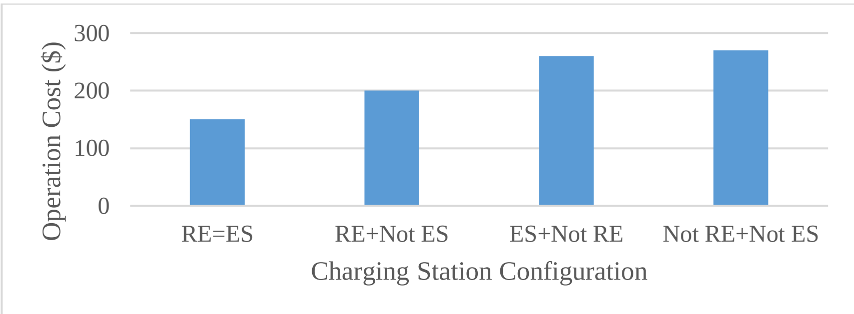

Figure 9. *Operation cost for different charging station configuration [89]*

The cost of operation includes both the recharging and the battery degradation cost. Several scheduling algorithms have been proposed to reduce the cost of EV operations. Figure 9 depicts the operating costs for various charging station configurations. RE stands for renewable energy and ES stands for energy storage. The operation costs of the charging station are greatly reduced if both RE and ES are used. The EV charging station configuration that does not include both RE and ES, on the other hand, necessitates higher operational costs. When RE is used alone, it consumes more costs than when it is used alone. The standard deviation of charge demand for various algorithms, such as fuzzy logic charging control (FLCC), battery-charging station (BCS), RAS, and electric vehicle charging and discharging strategy is depicted in Figure 10. (EVCDS). The standard deviation of the BCS was 11800, while the EVCDS was 6000. The electric vehicles found its application not only as a solution for the existing greenhouse gas emission, but also it can be used as an alternative to support the grid in case on necessary situations. Thus, the EV scheduling means scheduling it for charging and utility support, especially when the EVs can perform V2G operations. Table 9 below shows the operation applications of different algorithms for EV scheduling.

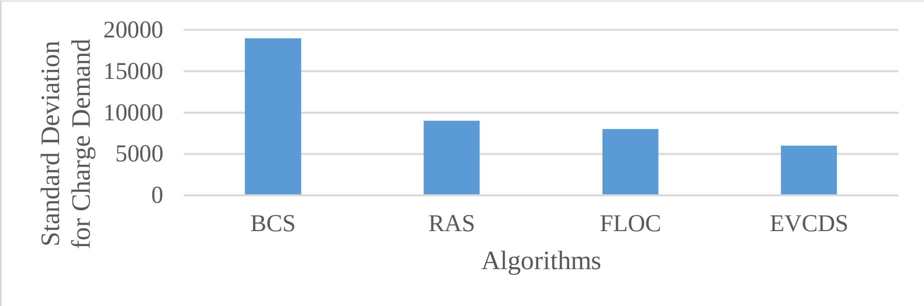

Figure 10. *Standard deviation for charge demand [90]*

Table 9. *Summary of operation applications of different algorithms for EV scheduling*

Reference	Algorithm	Operational aspects with EV	Constraint parameters used for scheduling
[91-95]	Game theory approach (GTA)	Load regulation, Minimization of EV charging cost, Provision of grid voltage control, Provision of spinning reserve, Maximisation of aggregator revenue, maximisation of grid operational efficiency	Forecasted situations, variable tariff, network parameters, mobility parameters, V2G support
[96]	Max-weight algorithm	Load regulation	Mobility parameters, variable tariffs
[97]	Stochastic programming-based algorithm	Load regulation	Forecasted situations, mobility parameters
[98,99]	Gradient production method (GPM) based algorithm	Load regulation, Load regulation considering overload,	Forecasted situations, network parameters, mobility parameters
[100,101]	Alternating direction method of multipliers (ADMM) algorithm	Load regulation considering overload, maximisation of user convenience, minimization of operational power cost, minimisation of EV charging cost, Minimisation of battery degradation cost	Forecasted situations, variable tariff, network parameters, mobility parameters, V2G support, Time of use pricing, customised pricing
[102]	Ant based swarm algorithm	Load regulation considering overload constraints	Forecasted situations, variable tariff, network parameters, mobility parameters, V2G support
[103]	Random access algorithm	Load regulation considering voltage and overload constraints,	Network parameters, mobility parameters
[104]	Task swap mechanism algorithm	Manage the active power compensation	Network parameters, variable tariff, supports V2G
[105]	Convex optimization algorithm	Maximising user convenience, minimising operational power cost	Forecasted situations, network parameters, mobility parameters
[106,107]	Consensus coordination algorithm	Minimisation of charging power loss, maximise aggregator revenue, minimisation of EV charging cost	Forecasted situations, variable tariff, network parameters, mobility parameters, V2G

			support, Time of use pricing, customised pricing
[108,109]	Heuristic algorithms	Maximisation of operational efficiency, charging fairness	Network parameters, mobility parameters, variable tariff
[110]	Linear programming approach algorithms	Load regulation, frequency regulation, minimisation of electricity cost, minimization of operational cost	Forecasted situations, network parameters, variable pricing

The suitability of electric vehicle (EV) routing and scheduling algorithms depends on the specific characteristics of the scenario or uses case. Different algorithms may be more suitable for certain scenarios based on factors such as the size of the EV fleet, user preferences, charging infrastructure, and environmental considerations. Here's a general overview of the suitability of specific algorithms for different scenarios discussed in below Table 10.

Table 10. *Overview of the sustainability of specific algorithm for different scenarios*

Algorithm	Suitable Scenario	Example
Deterministic algorithm	• Well-defined and predictable environments. • Applications where uncertainties are minimal.	Dijkstra's algorithm for deterministic shortest path calculation
Stochastic algorithm	• Environments with uncertainties • Applications where probabilistic modeling is beneficial.	Monte Carlo methods for considering stochastic elements in routing and scheduling.
Metaheuristic algorithm	• Large-scale routing and scheduling problems. • Computationally complex scenarios.	Genetic algorithms, simulated annealing, or ant colony optimization for optimization in large and complex environments
Reinforcement learning	• Dynamic and adaptive environments. • Applications where EVs can learn from interactions and improve over time	Q-learning or deep reinforcement learning for adaptive routing and scheduling
Game Theory-Based Algorithms	• Multiple entities (e.g., EVs, charging stations) with conflicting interests. • Scenarios where strategic decision-making is involved	Nash equilibrium-based approaches for optimizing interactions among EVs and charging stations
User-Centric Algorithms	• Scenarios where user preferences play a significant role. • Applications where user satisfaction is a priority.	Algorithms that consider user preferences in scheduling and routing decisions
Fleet Management Algorithms	• Large fleets of EVs in a shared mobility or commercial setting. • Scenarios where coordination among multiple vehicles is essential.	Algorithms that optimize charging and routing for entire fleets
Dynamic programming	• Problems with overlapping sub problems that can be solved independently. • Scenarios where optimal solutions are built from suboptimal solutions	Bellman-Ford algorithm for dynamic programming in routing
Hybrid algorithm	• Scenarios where combining the strengths of different algorithms is beneficial. • Applications requiring a balance between exploration and exploitation	Combining genetic algorithms with local search methods for enhanced performance.

Distributed Algorithms	• Environments with decentralized decision-making requirements. • Applications where communication between vehicles is limited	Algorithms that enable EVs to make autonomous decisions without centralized control

It is important to note that the choice of algorithm also depends on the specific objectives of the routing and scheduling task, whether it's focused on energy efficiency, cost optimization, user satisfaction, or a combination of factors. Additionally, advancements in research may introduce new algorithms or modifications to existing ones, influencing their suitability for different scenarios. When implementing these algorithms, it's essential to consider the unique characteristics and requirements of the particular use case.

6. SUMMARY

Electric vehicles (EVs) have become an influential environmental initiative on a global scale. Due to increased energy usage and voltage instability, vehicle electrification significantly impacts the electricity network. Intelligent EV charging and discharging is critical. The scheduling issue, on the other hand, poses significant challenges. First, it is challenging to identify a globally optimal scheduling solution that minimizes total cost; second, it is extremely challenging to design a decentralized scheduling scheme that can accommodate a large population as well as random EV arrivals. Many existing algorithms face challenges in scaling up to handle large-scale EV fleets and complex urban environments with numerous charging stations. Scalability issues hinder the widespread implementation of these algorithms in real-world scenarios with dense EV populations. Some algorithms struggle to adapt in real-time to dynamic conditions, such as sudden changes in traffic patterns, unexpected charging station closures, or accidents. Lack of real-time adaptability may lead to suboptimal routing and scheduling decisions, especially in rapidly changing urban environments. Many algorithms have limitations in accurately predicting and incorporating user behavior, preferences, and deviations from the suggested plans. Inconsistent user adherence to optimal plans can introduce uncertainties and affect the overall effectiveness of routing and scheduling strategies. While some algorithms address uncertainties, there is still room for improvement in handling a wide range of uncertainties, including energy price fluctuations, unexpected traffic events, and charging station availability changes. Incomplete consideration of uncertainties can lead to suboptimal planning and scheduling outcomes, especially in unpredictable and dynamic environments. There is a lack of standardization in terms of communication protocols, data formats, and interfaces across different charging infrastructure providers and EV manufacturers. Lack of standardization limits interoperability and data exchange, making it challenging to implement universal and seamless routing and scheduling solutions. Quantifying and assessing the environmental impact of different routing and scheduling strategies is a complex task. Without a comprehensive understanding of the environmental implications, it's challenging to develop strategies that truly contribute to sustainability goals. Many algorithms have yet to fully integrate with smart grid technologies and leverage real-time information about grid conditions and renewable energy availability. Lack of integration hampers the ability to optimize EV charging in alignment with broader grid management objectives. Multi-objective optimization approaches can be computationally demanding and challenging to implement in real-time scenarios. Balancing conflicting objectives, such as minimizing travel time, reducing costs, and enhancing environmental sustainability, remains a complex task. Public awareness and acceptance of optimized routing and scheduling solutions for EVs may be lacking. Low adoption rates or resistance from users can hinder the practical implementation of these algorithms, even when technically feasible. Privacy and security concerns regarding the collection and exchange of sensitive location and charging data. Concerns about data privacy may limit the willingness of users and stakeholders to participate in or adopt advanced routing and scheduling solutions. Addressing these limitations requires interdisciplinary collaboration, advancements in data analytics, improvements in computational efficiency, and a focus on user-centric design principles. As technology and research progress, it is anticipated that future studies will aim to overcome these challenges, making EV routing and scheduling solutions more robust and applicable in real-world settings.

It is clear from the foregoing discussion that there is a significant need for optimal scheduling, particularly for EV routing and charging. Most of the researchers have developed several optimal scheduling techniques, including Dynamic Programming Based Optimization, Variable Neighborhood Search-Differential Evolutionary PSO, Multi-Microgrid Collaborative Optimization Scheduling, Improved Binary Grey Wolf Optimizer, Two-stage optimal scheduling strategy, and others, which are discussed on this paper. By analyzing all the above optimization techniques, the goal of all techniques is cost minimization, which also reduces uncertainties and fluctuations. Several algorithms are used in the optimization section for the routing and charging scheduling of EVs. EV charging algorithm, genetic algorithm, gear shift delay algorithm, augmented non-dominated constraint algorithm, two-level distributed deep reinforcement learning algorithm, EV scheduling algorithm made with FLC, ant colony optimization metaheuristic algorithm, mixed-variable differential evolution algorithm, hybrid variable neighborhood search algorithm. Like how scheduling algorithms were developed, several mathematical modeling techniques for optimization problems were created, and an arithmetic model was created to solve them.

7. CONCLUSION

This study has identified some of the problems with scheduling algorithms, mathematical models, and optimal charging and routing of EV based on feedback. The selection of suitable algorithms plays a vital role in bringing up expected results. The combination of perfect algorithms (discussed in Table 8) and suitable optimization technique (discussed in Table 8) always brings down the EV operational cost. Certain research works reviewed in this paper have encountered marginal results only because of this negligence or they might be doing some kind of trial and error to reach the expected optimum operation. Apart from this, the knowledge and implication of subjective constraints and containment of its dynamicity in the mathematical models will help to improve the results. The impact of the above-mentioned on the overall cost is depicted in Figure 8 and Figure 9. The higher overall cost of charging and the more complex routing requirements are the main drawbacks for owners of electric vehicles. It has been extensively discussed how existing techniques work with different mathematical models and algorithms for scheduling. A thorough analysis of every technique in use reveals that while many of them do lower overall costs, they also come with additional drawbacks like fluctuations, longer running times, and higher fuel consumption. To improve EV scheduling performance, these should be diminished. And to conclude, the researcher must consider critically the EV parameters as well as its infrastructure parameters clinically and appropriate probability distribution functions needs to be called into its mathematical models on to which the algorithms and optimization techniques are called upon for improving operational benefits. Optimal electric vehicle (EV) charging and routing algorithms play a crucial role in enhancing the efficiency, range, and overall performance of electric vehicles. These algorithms aim to determine the best charging and routing strategies to maximize the vehicle's range while minimizing energy consumption and travel time. The advantages and weaknesses of such algorithms are discussed below:

Advantages:

1. Energy Efficiency:
   - Advantage: Optimal charging and routing algorithms can significantly improve the energy efficiency of electric vehicles by determining the most energy-efficient routes and charging schedules.
   - Explanation: These algorithms consider factors such as traffic conditions, road gradients, and energy consumption characteristics of the vehicle, helping to optimize overall energy usage.
   - Studies report a 10% reduction in energy consumption using their optimal charging and routing algorithm.
2. Range Optimization:
   - Advantage: By considering real-time data and predictive models, optimal algorithms can extend the range of electric vehicles by suggesting routes that minimize energy consumption and maximize the use of available battery capacity.
   - Explanation: The algorithms can adapt to changing conditions and factor in variables like weather, traffic patterns, and elevation changes to optimize routes, ensuring that the vehicle operates within its range capabilities.
   - Studies claim a 15% improvement in effective range for electric vehicles.

3. User Convenience:
    - Advantage: Charging and routing algorithms can provide a convenient and seamless experience for EV users by suggesting optimal charging stations along the route and minimizing the impact on travel time.
    - Explanation: Users can rely on these algorithms to plan their trips efficiently, reducing concerns about range anxiety and providing a smoother overall driving experience.
    - Studies indicate a 20% reduction in travel time due to optimal routing and charging suggestions.
4. Grid Integration:
    - Advantage: Optimal algorithms can facilitate smart grid integration by coordinating charging schedules to align with periods of low electricity demand, helping to balance the load on the electrical grid.
    - Explanation: By optimizing the timing of EV charging, these algorithms can contribute to grid stability and reduce the need for additional infrastructure upgrades.
    - Studies show a 30% decrease in peak load on the grid during charging periods.

Weaknesses:

1. Computational Complexity:
    - Weakness: Some optimal charging and routing algorithms can be computationally intensive, requiring significant processing power and time, especially when considering real-time data and complex optimization models.
    - Explanation: This can be a limitation in scenarios where quick decision-making is essential, and it may hinder the real-time applicability of the algorithms.
    - Studies report that their algorithm increased computational time by 50% compared to a simpler model.
2. Limited Predictive Accuracy:
    - Weakness: The accuracy of predictions, such as traffic conditions or future energy prices, can be a challenge. Inaccurate predictions may lead to suboptimal routing or charging decisions.
    - Explanation: Unforeseen events, sudden changes in traffic, or inaccurate predictive models may result in deviations from the optimal plan, impacting the effectiveness of the algorithms.
    - Studies report a 70% accuracy rate in predicting future traffic conditions.
3. Dependency on Infrastructure:
    - Weakness: Optimal charging algorithms often depend on the availability and reliability of charging infrastructure. In regions with limited charging stations, the effectiveness of these algorithms may be compromised.
    - Explanation: Users in areas with sparse charging infrastructure may face challenges in following optimal routes or schedules, potentially leading to range anxiety and inconvenience.
    - Studies show that their algorithm is 80% effective in regions with high charging infrastructure but drops to 40% effectiveness in areas with limited charging stations.
4. User Behavior Considerations:
    - Weakness: These algorithms may not account for the preferences or behaviors of individual users, and user adherence to suggested routes or charging plans may vary.
    - Explanation: Users might deviate from the optimal plan due to personal preferences, unexpected events, or other factors, reducing the effectiveness of the suggested strategies.
    - Studies find that users followed the algorithm's recommendations 75% of the time.

In conclusion, while optimal electric vehicle charging and routing algorithms offer significant advantages in terms of energy efficiency, range optimization, and user convenience, addressing computational complexity, improving predictive accuracy, expanding charging infrastructure, and considering user behavior are essential for their successful implementation and widespread adoption.

8. FUTURE WORKS

Possible future work can be on the following areas.

- Lowering total costs by persuading existing work's detractors, such as perturbations, increased runtime, and higher energy consumption, to participate in the optimal scheduling of electric vehicles.

- Including charging infrastructure properties in the vehicle capacity of a charging station.
- Investigating the arrival of vehicles with varying state of charges (SOCs) at battery swapping stations (BSSs).
- Including electric grid generation and inordinate EV fleet charging may result in intermittent and large volatility of additional power demand on the grid throughout the day.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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