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Review

A Review on Optimizing Electric Vehicle Charging Schedules for Cost and Grid Efficiency

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Abstract: The rapid growth of electric vehicles has introduced new operational and economic challenges for modern power systems, including charging demand management, grid stability, peak load reduction, and cost control. To address these issues, various optimization strategies have been proposed, including heuristic and metaheuristic algorithms, exact mathematical programming models, and data-driven approaches. Heuristic and metaheuristic methods such as Genetic Algorithms, Particle Swarm Optimization, and evolutionary algorithms are widely used because of their flexibility and ease of implementation. However, they may suffer from parameter sensitivity, limited reproducibility, and the absence of guaranteed optimality. In contrast, exact optimization approaches, particularly Mixed-Integer Linear Programming, provide a structured framework for modeling constraints such as charging power limits, state-of-charge requirements, transformer capacity, dynamic pricing, and vehicle-to-grid interactions. This review examines studies published after 2020 and compares solver-based, heuristic/metaheuristic, and data-driven approaches for electric vehicle charging scheduling in terms of cost efficiency, grid impact, scalability, constraint handling, and practical applicability. Rather than presenting new computational experiments, the paper synthesizes reported findings from the literature and discusses the conditions under which solver-based methods, including IBM CPLEX, are advantageous or limited. The reviewed studies suggest that solver-based methods are useful for constraint-rich and reproducible scheduling formulations, while heuristic and data-driven methods remain attractive for large-scale, uncertain, or real-time applications. The review highlights unresolved gaps, including limited standardized benchmarks, insufficient empirical comparison across common test systems, weak integration of battery degradation and user behavior, and a lack of realistic uncertainty and grid-aware modeling.

***Keywords*:** charging schedule, cost efficiency, electric vehicle optimization, grid efficiency

1. Introduction

The rapid increase in Electric Vehicles (EVs) has created major challenges for today's power systems. Global EV sales have surged in the past decade, surpassing 10 million in 2022 and reaching 14% of all new car registrations, up from 4% in 2020 [1]. By 2030, more than 200 million EVs are expected worldwide, representing nearly one-third of all new vehicles sold [2]. This growth is driven by advances in battery technology, declining lithium-ion costs, supportive government policies, and rising environmental awareness. Yet large-scale EV deployment also introduces significant technical and economic challenges for the grid. Without coordinated charging, stable grid operations can become volatile

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and unpredictable. Furthermore, recent literature emphasizes that the rapid proliferation of EVs introduces broader socio-economic and infrastructural trade-offs, particularly in emerging markets, requiring careful policy and grid management [3]. Uncontrolled EV charging leads to higher peaks, stress on distribution transformers, and increased operating costs [4, 5]. As a result, developing effective and scalable EV-charging management strategies has become a major research priority for both academia and industry [6].

To address these challenges, researchers have explored heuristic algorithms, metaheuristics such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), simulation-based planning, and mathematical programming approaches like Mixed-Integer Linear Programming (MILP). These methods have provided valuable insights into cost minimization, peak load reduction, and user satisfaction. Still, a clear gap remains: the limited use of commercial solvers such as IBM CPLEX, which are built for large-scale, constraint-rich scheduling problems and can deliver guaranteed optimal solutions [7, 8]. Recent evidence also shows that hybrid frameworks combining MILP with machine learning or heuristic preprocessing can further enhance scalability and adaptability. In addition, comprehensive reviews have summarized charging scheduling, fleet management, and charging station planning in electrified Demand-Responsive Transport (DRT) systems, providing a broad methodological overview of the field [9].

In addition, while some studies have incorporated time-of-use tariffs, uncertainty modeling, or Vehicle-to-Grid (V2G) services, these elements are usually examined separately, which limits their real-world relevance [10, 11]. Stochastic and robust optimization approaches offer useful tools for handling such uncertainties by explicitly modeling dynamic pricing, stochastic arrivals, and renewable variability [12–14]. In this review, particular attention is given to solver-based formulations, especially MILP models solved with IBM CPLEX. Evidence suggests that combining realistic tariffs, grid constraints, uncertainty modeling, and user behavior with exact optimization can produce schedules that are more reliable and scalable than those generated by heuristic methods [7, 8, 15, 16]. Taken together, these findings point to the need for research that jointly addresses cost minimization, grid-aware constraints, user behavior, and systematic solver benchmarking.

This review surveys the state of the art in EV charging optimization, with an emphasis on how IBM CPLEX and other solver-based methods have been applied to connect theoretical models with practical applications. By comparing solver-based and non-solver approaches, highlighting gaps in the literature, and outlining emerging directions, the paper offers a structured overview for future studies in this field. Beyond solver-based scheduling, complementary studies emphasize spatial and sustainability aspects of EV infrastructure. For instance, GIS- and network-based approaches have been applied for location planning [17, 18], while renewable energy integration through PV deployment has also been highlighted as a pathway toward sustainable charging [19, 20].

1.1 *Background and problem statement*

The growing adoption of EVs is reshaping power systems, turning predictable one-way energy flows into dynamic, bidirectional exchanges. This transition creates operational challenges such as higher peak loads, voltage instability, and accelerated transformer aging during periods of uncoordinated charging. For instance, Yao et al. [10] showed that in urban networks with more than 300 EVs per feeder, uncontrolled charging increased peak demand by 25%, hastening transformer wear and raising line losses. Likewise, Zhao and Liang [21] reported voltage deviations greater than ±5% during simultaneous evening charging, highlighting risks to grid stability.

EV charging scheduling focuses on selecting charging times and power levels that minimize costs, enhance grid performance, and satisfy user requirements. Typical approaches use Mixed-Integer Linear Programming (MILP) or Mixed-Integer Nonlinear Programming (MINLP), incorporating detailed constraints such as transformer capacity, state-of-charge limits, station availability, and time-of-use tariffs [7, 8]. Adding Vehicle-to-Grid (V2G) operations increases complexity by allowing bidirectional flows. Hematian et al. [22] showed that including V2G in MILP models reduced peak demand by up to 15%, while [4] found that dynamic pricing shifted charging to off-peak hours.

In addition to grid-related challenges, road network constraints such as slope, road class, and pavement type also influence the accessibility and feasibility of charging infrastructure. For example, Erener and Şirin [23] demonstrated through a Python-based network analysis that such parameters significantly affect micromobility and electric transport accessibility.

Despite these advances, many studies continue to rely on heuristic or metaheuristic methods. These techniques are computationally efficient but often fall short in scalability and in providing provably optimal solutions for large, constraint-heavy systems [24, 25]. In contrast, solver-based methods, particularly MILP formulations, have proven effective at handling complex operational constraints and producing reliable results. Recent work has applied solvers such as IBM CPLEX and Gurobi, but their use in EV scheduling is still less common than heuristic approaches.

2. General methods

This section classifies and critically examines the main methodological approaches to EV charging optimization found in the literature, emphasizing their strengths, limitations, and representative studies. Research on Electric Vehicle (EV) charging optimization encompasses a variety of methodologies, each addressing different dimensions of the scheduling problem, including cost minimization, grid stability, and user convenience. Recent systematic reviews have approached this field from different perspectives. Guerrero-Silva et al. [6] applied a PCA-based framework to capture infrastructure optimization trends, while [26] provided a comprehensive overview of charge scheduling techniques and security concerns. Al-Alwash et al. [27] contrasted centralized and decentralized scheduling schemes, examining both classical and machine-learning-based optimization methods with a focus on computational complexity and scalability. Complementing this, Elghanam et al. [28] delivered a systematic PRISMA-based classification spanning time-based, spatial, and spatio-temporal coordination models, highlighting both solver-based deterministic formulations and heuristic/metaheuristic alternatives. Previous studies have also summarized optimization techniques ranging from MILP and heuristic-based scheduling to reinforcement learning approaches for EV fleet and charging management, providing a strong foundation for methodological comparisons [9]. Accordingly, methodologies can be broadly categorized into three main groups:

i. Exact optimization techniques;

ii. Heuristic and metaheuristic approaches;

iii. Data-driven predictive frameworks.

In order to clarify their contributions, this section highlights typical cost functions (e.g., energy cost, peak demand penalties, waiting time, emissions) and key constraints (e.g., transformer capacity, voltage limits, user arrival/departure times, V2G feasibility) associated with each class of methods. While the details vary across studies, a few representative cases illustrate the distinct capabilities and limitations of each methodological family.

2.1 *Generic formulation of the EV charging scheduling problem*

EV charging scheduling can generally be formulated as an optimization problem in which charging and, when applicable, discharging power are allocated to electric vehicles over a discrete time horizon. The main objective is to minimize the total charging cost while satisfying user requirements and technical grid constraints. Although the reviewed studies differ in their assumptions, solution methods, and application scales, a generic formulation of the EV charging scheduling problem can be expressed as follows:

$$\min\ Z = \sum_{t\in T} c_t P_t \Delta t + \lambda \max_{t\in T} P_t + \sum_{i\in N} C_i^{\text{deg}},$$

where N denotes the set of electric vehicles and T represents the set of discrete time intervals. The first term represents the total electricity cost over the scheduling horizon, where c_t is the electricity price at time interval t, P_t is the aggregate charging demand, and Δt is the duration of each time interval. The second term penalizes the peak aggregate power demand, where λ is the peak demand penalty coefficient. The third term represents the battery degradation cost, which becomes particularly relevant when Vehicle-to-Grid (V2G) operation or repeated charging and discharging cycles are considered.

In a unidirectional charging case, the aggregate charging demand can be defined as:

$$P_t = \sum_{i \in N} P_{i,t}^{ch},$$

where $P_{i,t}^{ch}$ is the charging power of vehicle i at time interval t. When V2G operation is included, the net power exchanged with the grid can be represented as:

$$P_t = \sum_{i \in N} \left(P_{i,t}^{ch} - P_{i,t}^{dis} \right),$$

where $P_{i,t}^{dis}$ denotes the discharging power of vehicle i at time interval t. The state-of-charge dynamics of each vehicle can be written as:

$$SOC_{i,t+1} = SOC_{i,t} + \eta_i^{ch} P_{i,t}^{ch} \Delta t - \frac{1}{\eta_i^{dis}} P_{i,t}^{dis} \Delta t,$$

where $SOC_{i,t}$ is the state of charge of vehicle i at time interval t, while η_i^{ch} and η_i^{dis}denote the charging and discharging efficiencies, respectively. The state of charge must remain within its minimum and maximum allowable limits:

$$SOC_i^{\min} \leq SOC_{i,t} \leq SOC_i^{\max}, \quad \forall i \in N, \forall t \in T.$$

The charging and discharging powers are also bounded by the technical limits of the charger and the vehicle battery system:

$$0 \leq P_{i,t}^{ch} \leq P_i^{ch,max}, \quad \forall i \in N,\ \forall t \in T,$$

$$0 \leq P_{i,t}^{dis} \leq P_i^{dis,max}, \quad \forall i \in N,\ \forall t \in T.$$

In addition, the aggregate power demand should not exceed the available grid or transformer capacity. For V2G-enabled operation, this constraint can be written as:

$$\sum_{i \in N} P_{i,t}^{ch} \leq P_t^{grid,max}, \qquad \forall t \in T$$

$$\sum_{i \in N} \left(P_{i,t}^{ch} - P_{i,t}^{dis} \right) \leq P_t^{grid,max}, \quad \forall t \in T.$$

Finally, each vehicle must reach the required state of charge before its departure time:

$$SOC_{i,d_i} \geq SOC_i^{req}, \quad \forall i \in N,$$

where d_i denotes the departure time of vehicle i, and SOC_i^{req} represents the minimum required state of charge at departure. This generic formulation provides a common mathematical basis for comparing solver-based, heuristic, metaheuristic, and data-driven approaches in the reviewed literature. Solver-based methods such as MILP models solved by CPLEX or Gurobi directly handle these objective terms and constraints, whereas heuristic and data-driven methods often approximate or relax some of these constraints to improve computational speed and flexibility.

2.2 *Exact optimization approaches*

A 'solver' is a specialized computational engine designed to find the optimal solution to mathematical models (like MILP). It uses advanced algorithms, such as branch-and-bound, to systematically search through possible options while respecting all defined constraints. In EV charging, commercial solvers like IBM CPLEX transform complex grid limits and costs into precise, actionable charging schedules.

Exact optimization methods, most often based on Mixed-Integer Linear Programming (MILP) or Mixed-Integer Nonlinear Programming (MINLP), seek globally optimal solutions using formal mathematical models. These approaches typically aim to minimize charging costs, sometimes combined with peak demand penalties or carbon emission targets, while respecting grid capacity, charging limits, and time windows. Recent MILP studies have focused on siting and scheduling problems [7, 8], grid-constrained formulations [29, 30], and integrated routing or tariff-aware models [31, 32]. The overall methodological landscape and the interplay among the three main approaches are illustrated in Figure 1.

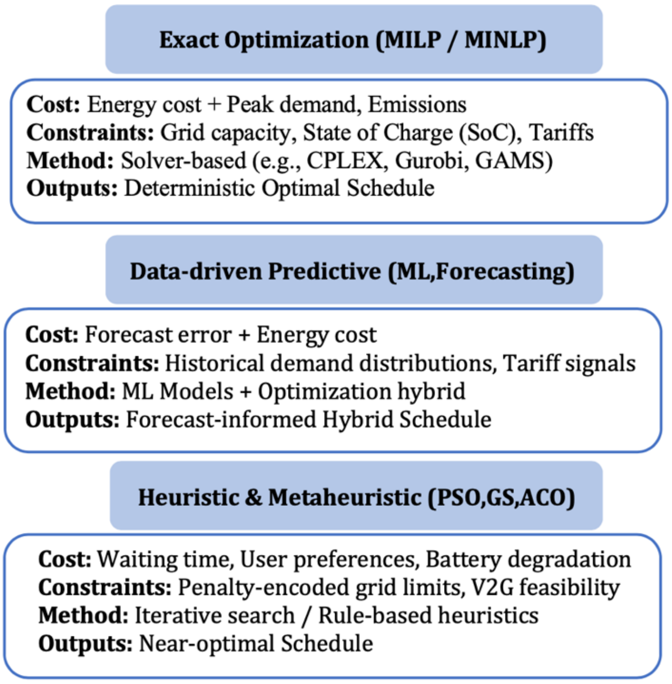

Figure 1. Methodological landscape of EV charging optimization

For example, an MILP model for EV station siting and scheduling was developed, where the objective combined infrastructure investment cost with operational charging cost [8]. The model, solved using a commercial solver, achieved high computational efficiency and scalability for urban networks. Similarly, Sabzi and Vajta [7] incorporated V2G operations and dynamic pricing into a MILP framework, where the objective was to minimize energy cost plus peak penalties, subject to transformer capacity and user time-of-departure constraints. In another case, Maigha and Crow [30] compared static and dynamic MILP-based charging formulations solved with CPLEX under different tariff schemes, demonstrating that dynamic real-time optimization can achieve near-optimal results with significantly lower runtime, making it more practical for operational deployment. Ham and Park [32] formulated the EVRPTW under time-of-use electricity pricing using MIP, CP, and a hybrid MIP-CP approach, demonstrating that CPLEX-based exact optimization can strategically shift charging to off-peak periods and achieve significant cost reductions. The joint routing and charging of EV fleets was formulated as a MIQCP, showing that commercial solvers such as CPLEX and Gurobi can effectively incorporate passenger satisfaction, charging prices, and battery dynamics into large-scale transit optimization [32].

Building on this, a two-stage MILP framework combined with a Design and Analysis of Computer Experiments (DACE) approach was proposed for optimizing EV charging station systems. Using Multivariate Adaptive Regression Splines (MARS) with a binned Latin Hypercube sampling design, near-optimal results (≤1% profit loss) were achieved while cutting runtime from several hours with Gurobi to about 18 minutes [8]. This shows that MILP combined with metamodel-assisted optimization can greatly speed up computation while preserving solution quality.

A two-stage robust MILP framework for microgrid management that integrates EV charging, renewable energy, demand response, storage systems, and compensators was introduced and solved with a Column-and-Constraint Generation (C&CG) algorithm. The results showed that robust optimization can improve both cost efficiency and grid feasibility under high uncertainty [33]. In the same direction, Karimianfard developed a two-stage robust MILP for smart home energy management, integrating EV charging, PV-battery storage, and demand response under TOU/RTP tariffs. Using the C&CG algorithm, the study reported higher cost efficiency and feasibility compared to deterministic models [34]. Although solver-based methods are often computationally demanding, they provide reliable, constraint-compliant, and reproducible outcomes, qualities that are particularly important in policy-oriented and large-scale system studies.

2.3 *Heuristic and metaheuristic methods*

Heuristic and metaheuristic approaches encompass problem-specific rules (heuristics) and general-purpose iterative search algorithms (metaheuristics such as PSO, GA, and ACO). These methods are particularly attractive when exact formulations are computationally impractical. Their cost functions often extend beyond energy cost to include user waiting times, battery degradation, or multi-objective trade-offs between grid stress and economic efficiency [24, 25]. Constraints such as transformer capacity or voltage limits are generally incorporated via penalty terms or customized encoding schemes, which may compromise strict feasibility.

Particle Swarm Optimization was applied to minimize both charging cost and network stress [24]. A game-theoretic heuristic for decentralized charging was employed, where the cost function balanced individual user cost with overall system stability [25]. In another example, Metaheuristic algorithms (PSO, SSA, AOA) were applied to optimize the design structure of EV fast-charging stations, including charger count, storage sizing, and renewable integration, showing effective near-optimal solutions highlighting the practical relevance of such heuristic methods despite their scalability and reproducibility challenges [35].

2.4 *Data-driven and predictive approaches*

With the proliferation of smart meters, IoT-enabled charging infrastructure, and dynamic tariffs, data-driven models have emerged as a complementary class of methods. These approaches employ Machine Learning (ML) and forecasting tools to model charging demand profiles, user preferences, and price responsiveness, which are then embedded into optimization frameworks. Typical cost functions in these approaches include forecasting error minimization (e.g., RMSE of demand prediction) combined with traditional energy cost objectives. Constraints frequently stem from historical data-based user arrival/departure distributions or real-time pricing signals.

For instance, a clustering-based demand forecasting model integrated with an MILP formulation was proposed, where predicted demand reduced the feasible search space and accelerated convergence [36]. Supervised learning was applied to infer user-specific departure times and price sensitivity, embedding these as explicit constraints in a scheduling model [37]. Hybrid frameworks have become increasingly common, such as MILP-GA combinations, which demonstrate how solver-based exactness and heuristic flexibility can be combined to reduce computational effort while retaining near-optimal results. Distributed EV charging control methods were surveyed, highlighting the importance of decentralized, data-driven coordination as a complement to solver-based scheduling [38]. More recently, incorporating L_2-norm-based uncertainty into robust optimization frameworks was shown to enhance cost efficiency and reliability, illustrating how predictive and robust paradigms can be merged with solver-based scheduling for improved scalability [39]. Beyond classical supervised and clustering-based methods, reinforcement learning approaches have also emerged. For instance, a deep reinforcement learning framework optimized charging schedules adaptively under dynamic grid conditions, demonstrating the potential of RL in capturing complex temporal patterns of EV demand [9]. Such approaches are particularly suited for uncertain and dynamic environments where purely mathematical models or purely heuristic methods fall short. An overall comparative overview of solver-based, heuristic, and data-driven methodologies is summarized in Table 1.

Table 1. Comparative overview of EV charging optimization methodologies

Methodology & Key features	Advantages	Limitations	Example studies
MILP (CPLEX): Exact mathematical optimization	Global optimality; scalable	High computational demand	[7, 8, 15, 29, 31, 32, 40–42]
Metaheuristics: Iterative, nature-inspired search	Flexible; suitable for multi-objective problems	No guarantee of optimality; high sensitivity to parameters and instances; complex constraint modeling	[10, 24, 25, 35, 38, 42–44]
Data-Driven (ML): Predictive modeling & hybridization (ML + MILP)	Adaptive; handles uncertainty; can reduce MILP computation time via pre-processing	Requires large datasets; interpretability challenges; hybrid integration may add modeling complexity	[16, 37, 38]
Comprehensive Review: Systematic classification across exact, heuristic, and ML approaches	Provides holistic comparison of methodologies and highlights research trends	Does not provide solver-specific benchmarks (e.g., CPLEX vs. Gurobi)	[26, 27]
Comprehensive Review (Spatio-Temporal): Compares deterministic solver-based and heuristic/metaheuristic approaches	Captures methodological diversity; bridges solver-based and non-solver-based perspectives; highlights spatio-temporal dimension	Does not provide detailed solver performance benchmarks; still limited in real-world validation	[28]

3. Results and discussion

3.1 *Solver evaluation and comparative analysis*

Building on the methodological classification from the previous section, the next step is to evaluate how these approaches perform under standardized conditions. A consistent assessment of optimization methods for EV charging requires a framework that considers both computational efficiency and solution quality across different operating scenarios. While heuristic and data-driven methods offer flexibility, solver-based approaches—especially those using commercial solvers such as IBM CPLEX, Gurobi, and GAMS—remain the main reference for producing reliable and scalable results [7, 8, 27].

Early work had already shown the effectiveness of CPLEX for EV fleet scheduling: linear formulations proved computationally efficient, whereas quadratic formulations captured battery dynamics but required much longer runtimes [13]. It was further noted that although LP and MILP models guarantee optimality, their complexity rises quickly as the number of EVs and system constraints grow [27]. Recent studies also reported that MIP and MIQP are still widely solved by CPLEX and Gurobi, though scalability remains a barrier for large spatio-temporal problems [28]. Finally, scenario-based stochastic MILP formulations solved with CPLEX were shown to reduce extreme load deviations compared to deterministic models, highlighting the robustness of solver-based methods under uncertainty.

Figure 2 illustrates the generic workflow followed in EV charging scheduling studies. The process begins with input data such as EV arrival and departure times, state-of-charge requirements, electricity tariffs, and grid constraints. These inputs are translated into an optimization model, which is then solved using exact, heuristic, or hybrid methods. The resulting schedules are subsequently evaluated using metrics such as runtime, optimality gap, cost saving, peak reduction, feasibility, and robustness.

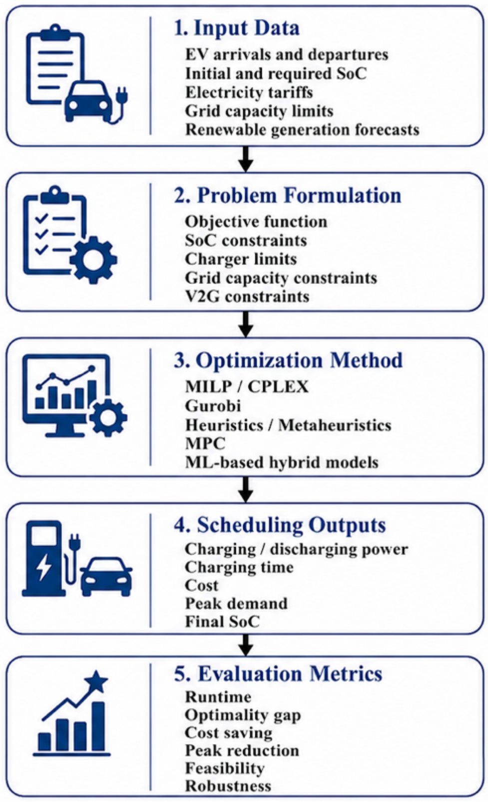

Figure 2. Generic framework for EV charging scheduling optimization and evaluation

This section identifies key evaluation metrics, including solution quality, optimality gap, computation time, scalability, and robustness. It also describes widely used benchmark datasets and provides a comparative analysis of solver-based and non-solver-based approaches.

3.1.1 *Solver evaluation metrics*

Evaluating optimization methods for EV charging scheduling requires a structured framework that accounts for both computational efficiency and solution quality under realistic operating scenarios. While heuristic and data-driven methods such as deep reinforcement learning offer adaptability and real-time responsiveness, solver-based approaches (MILP, CPLEX, Gurobi, GAMS) remain the benchmark for deterministic, scalable, and reproducible performance. Recent studies reinforce this view through different perspectives: MILP-based scheduling models have been shown to be superior [7, 8], scalability challenges have been emphasized [27], and solver effectiveness under stochastic and tariff-driven conditions has been demonstrated [32, 40]. The most widely used solver evaluation metrics and their representative applications are summarized in Table 2.

For example, MILP models solved with IBM CPLEX achieved a 95% reduction in optimality gap compared to heuristic methods in a 500-EV scheduling scenario, highlighting their superior convergence behavior [15]. Similarly, solver-based formulations converged 30% faster while preserving grid-constraint feasibility under high-penetration scenarios, a performance advantage not observed in metaheuristic approaches [7]. In addition, static and dynamic MILP formulations solved with CPLEX were compared under different tariff schemes, showing that dynamic real-time optimization achieved near-optimal performance with significantly reduced runtime, thereby enhancing the practical applicability of solver-based approaches [30]. It was further reported that while pure MIP models became computationally prohibitive for large binary formulations, a hybrid MIP-CP framework consistently achieved feasible schedules with lower runtime and cost, illustrating the potential of solver-based hybridization for improving scalability under time-of-use pricing conditions [32].

Beyond these studies, exact models were shown to incorporate voltage stability constraints without significant increases in computation time, whereas heuristic models required simplifications that often violated technical feasibility [28].

Table 2. Summarizes the most widely used metrics in the literature, their definitions, relevance to EV charging optimization, typical measurement approaches, and representative studies

Metric	Description	Measurement approach	Relevance	Example studies
Solution Quality	Degree to which the obtained solution matches the global optimum or the best-known bound.	Percentage deviation from optimum at solver termination.	Critical for benchmarking solver-based methods against heuristics lacking exact optimality checks.	[8, 29]
Optimality Gap	Difference between the solver's best feasible solution and its best-known lower bound.	Calculated as (UB−LB)/LB × 100%, where UB is upper bound and LB is lower bound.	Key indicator of solver convergence efficiency.	[7, 15]
Computation Time	Time taken to reach optimal or near-optimal solutions.	Measured in seconds or minutes, with or without predefined time limits.	Essential for real-time and large-scale deployments.	[45, 46]
Scalability	Solver performance as problem size increases.	Tested by incrementally increasing EV fleet size, charging stations, and time slots.	Determines feasibility for industrial-scale applications.	[21, 47]
Memory Usage	Computational resources required for solving.	Peak RAM usage during the solution process.	Relevant for large MILP problems with grid-level constraints.	[4, 48]
Robustness	Ability to maintain feasibility and performance under uncertainty.	Introducing stochastic variations in demand, arrivals, or pricing and measuring performance degradation.	Ensures resilience in real-world and stochastic scenarios.	[7, 46]

Stochastic arrival scenarios were evaluated, and solver-based methods reduced expected system cost by nearly 18% compared to GA-based scheduling [49]. The integration of time-of-use pricing was emphasized, and solver-based formulations achieved more stable peak load reductions across multiple tariff schemes, while PSO and ACO displayed inconsistent performance across runs [11].

Moreover, it has been highlighted that solver-based methods facilitate standardized benchmarking, enabling reproducibility and comparability across case studies, which remains a challenge for metaheuristics due to their dependence on initialization and parameter tuning [8]. Finally, hybrid ML + solver models were demonstrated to improve scalability and forecast accuracy, showing that exact formulations can effectively integrate predictive demand profiles, an area where heuristics struggle to capture uncertainty [38]. Collectively, these findings indicate that while heuristics provide flexibility and lower computation in smaller test systems, solver-based approaches consistently outperform in convergence speed, constraint feasibility, and reproducibility, especially in large-scale or policy-driven contexts.

To address the need for a more concrete comparative basis, Table 3 summarizes representative numerical findings reported in the reviewed literature. Since this paper is designed as a review article rather than an original benchmarking study, the values are not generated from a new controlled experiment. Instead, they are extracted from published studies to illustrate how solver-based, heuristic/metaheuristic, and hybrid approaches differ in terms of problem scale, computation time, optimality gap, cost reduction, peak-load reduction, and dataset or test-system selection. This literature-derived comparison helps clarify the practical meaning of evaluation metrics such as solution quality, scalability, and computational efficiency.

Table 3. Literature-derived numerical comparison of EV charging optimization methods

Study	Method/Model	Solver/Algorithm	Problem scale/Test system	Runtime	Optimality gap/solution	Reported benefit	Main limitation
[13]	LP/QP-based EV fleet charging	CPLEX	EV fleet charging under constrained grid conditions	LP faster; QP longer runtime	Optimal for formulated model	Demonstrated the suitability of mathematical programming for coordinated EV charging	Early study; limited modern V2G and uncertainty modeling
[30]	Static and dynamic EV charging optimization	CPLEX	EV charging under tariff constraints	Dynamic formulation reduced runtime compared with full static optimization	Near-optimal solution reported	Lower charging cost and improved operational practicality	Older study; limited large-scale benchmark standardization
[32]	EV routing with charging under TOU pricing	MIP, CP, hybrid MIP-CP	EV routing problem with time windows	Hybrid MIP–CP reduced computational burden	Feasible/near-optimal schedules	Off-peak charging and route-cost reduction	Routing-specific formulation; not directly comparable with grid feeder studies
[8]	Two-stage MILP with computer experiments	Gurobi/MILP + DACE	EV charging station system optimization	Reduced from several hours to about 18 min	≤1% profit loss	Strong runtime reduction while preserving near-optimality	Focused on station system design rather than real-time operation
[22]	Robust optimization for microgrid and EV integration	Robust MILP/optimization framework	Microgrid with EV storage, renewables, demand response	NR	Robust feasible solution	Improved feasibility under uncertainty	Requires complex uncertainty modeling
[24]	Scenario-based stochastic charging scheduling	Stochastic optimization	EV availability and charging demand uncertainty	NR	Reduced deviations compared with deterministic scheduling	Better uncertainty handling	Computational burden increases with scenario number
[24]	Metaheuristic EV charging scheduling	PSO/SSA/AOA	EV charging scheduling simulation	Fast convergence reported	No global optimality guarantee	Flexible and suitable for large search spaces	Sensitive to algorithm parameters and repeated runs
[43]	EV routing optimization	Tabu Search	EV routing problem	Lower runtime than exact methods	Comparable solution quality reported	Strong computational efficiency	No proof of global optimality
[37]	Adaptive charging/data-driven scheduling	ACN-based optimization framework	Real EV charging network	Application-dependent	Practical feasibility	Captures real user charging behavior	Site-specific dataset; generalization may be limited
[38]	Distributed EV charging control survey	Distributed algorithms	Smart grid charging control	NR	NR	Highlights decentralized scalability	Not a direct numerical benchmark
[39]	Robust EV charging with L_2-norm uncertainty	Robust optimization	Fast EV charging under uncertainty	NR	Robust feasible solution	Improved cost efficiency and reliability	Requires further empirical validation on physical distribution grid infrastructure

Note: NR indicates that the corresponding numerical value was not explicitly reported in the reviewed study. The table is intended to provide a literature-derived comparison rather than a controlled benchmark performed by the authors

The comparison in Table 3 shows that solver-based approaches are generally strongest when strict constraint satisfaction, reproducibility, and optimality guarantees are required. However, their computational performance depends strongly on the mathematical structure of the model, the number of binary variables, the size of the EV fleet, the number of time intervals, and the inclusion of nonlinear battery or grid constraints. Metaheuristic methods generally provide faster approximate solutions, but their lack of optimality-gap information and sensitivity to parameter settings make cross-study comparison difficult. Hybrid approaches, particularly those combining MILP with predictive models, decomposition, or heuristic preprocessing, appear promising because they can reduce computation time while retaining much of the modeling rigor of exact optimization. Nevertheless, the comparison also reveals a major limitation in the literature: many studies do not report complete benchmarking information such as runtime, memory usage, optimality gap, solver settings, or standardized test cases. This lack of reporting limits the reproducibility and comparability of EV charging scheduling research.

3.1.2 *Benchmark datasets*

Benchmark datasets are integral to enabling reproducibility and fair comparison across EV charging optimization studies. Simulation platforms such as ACN-Sim provide modular, open-source environments that support charging algorithms under realistic network and behavioral dynamics. For example, IEEE 33-bus test data combined with real-world pricing signals demonstrated that solver-based MILP models achieved 12% cost savings compared to metaheuristics in a V2G-enabled scheduling scenario [22]. Similarly, synthetic EV datasets coupled with clustering-based forecasting were employed to enhance a hybrid MILP–ML framework, improving computational efficiency while preserving solution quality [37]. Supervised learning was also integrated to capture user-specific departure times and price sensitivity, showing that embedding behavioral constraints into solver-based models improved both scalability and user satisfaction [38]. A summary of the most frequently used benchmark datasets and their representative applications is provided in Table 4.

Benchmark datasets and test systems are essential for improving reproducibility and enabling fair comparison among EV charging scheduling methods. However, the reviewed literature shows that many studies still rely on synthetic EV profiles, isolated tariff scenarios, or customized test systems, which makes direct comparison difficult. Therefore, this review distinguishes between real-world charging datasets, standardized distribution network test feeders, public tariff databases, and synthetic fleet datasets. Table 4 summarizes representative datasets and test systems that are frequently used or recommended for EV charging optimization studies.

Real-world tariff and load datasets were applied to compare solver-based optimization with GA and PSO, finding that exact models consistently achieved lower peak loads (≈15% reduction) and better cost-to-grid trade-offs [9]. Real-time scheduling on an IEEE 13-node feeder was also evaluated, demonstrating that MILP-based approaches maintain grid feasibility while ensuring full PEV charging commitments. Likewise, it was demonstrated that under V2G and dynamic pricing conditions, solver-based approaches exhibited more stable convergence across stochastic arrival patterns than metaheuristic baselines [7].

These examples collectively highlight the importance of dataset choice and scenario design, whether synthetic test feeders, real-world tariffs, or user behavior surveys not only for validating model performance but also for ensuring that reported improvements can be attributed to the optimization methodology itself rather than to differences in input assumptions.

As shown in Table 4, benchmark selection strongly influences the reported performance of EV charging scheduling methods. Real-world charging datasets such as ACN-Data and JPL charging sessions are valuable for capturing user behavior, but they may not include detailed distribution-grid constraints. In contrast, IEEE distribution feeders provide standardized grid models for evaluating voltage stability, transformer loading, and feeder-level constraints, but they usually require synthetic EV arrival and charging demand profiles. Public tariff databases such as OpenEI support realistic cost modeling, whereas NREL and scenario-based datasets are useful for renewable integration and uncertainty-aware scheduling. Therefore, a comprehensive benchmark framework should ideally combine real charging-session data, standardized grid feeders, realistic tariff structures, and uncertainty scenarios. This would allow solver-based, heuristic/metaheuristic, and data-driven methods to be compared under more consistent and reproducible conditions.

Table 4. Benchmark datasets and test systems used in EV charging optimization studies

Dataset/Test system	Type	Main data/Variables	Accessibility/Source type	Strengths	Limitations	Typical use in EV charging studies	Related studies
ACN-Data/Caltech Adaptive Charging Network	Real-world EV charging dataset	Plug-in time, unplug time, delivered energy, charging duration, station-level charging behavior	Publicly available research dataset	Captures realistic user charging behavior and station utilization patterns	Site-specific; mainly reflects workplace / institutional charging behavior	User behavior modeling, adaptive charging, demand forecasting, validation of scheduling algorithms	[37]
JPL ACN Dataset	Real-world EV charging dataset	Arrival time, departure time, energy demand, charging session duration, charging station usage	Publicly available through ACN-related data sources	Provides practical charging-session data from an operational EV charging network	Geographically and behaviorally limited to a specific charging environment	Realistic arrival/departure modeling, demand prediction, data-driven scheduling	[37]
IEEE 33-Bus Feeder	Standard distribution network test feeder	Distribution network topology, bus loads, line impedances, voltage limits	Standard benchmark system widely used in power systems	Commonly used for distribution-level power-flow and optimization studies	Requires assumed or synthetic EV arrival and charging demand profiles	Peak-load reduction, power loss minimization, transformer loading analysis	[22, 46]
IEEE 69-Bus Feeder	Standard distribution network test feeder	Larger radial distribution network, voltage profile, line losses, load flow data	Standard benchmark system	Useful for scalability testing in larger distribution systems	Still requires externally generated EV demand and tariff assumptions	Large-scale grid-aware EV charging coordination and feeder-level impact studies	[46]
OpenEI Utility Rate Database	Public tariff/electricity price database	Time-of-use tariffs, demand charges, utility electricity rates, regional tariff structures	Public energy data platform	Enables realistic cost modeling under TOU and dynamic pricing schemes	Tariffs are region-specific and may require preprocessing	Cost minimization, tariff-aware scheduling, demand-response modeling	[11]
NREL Transportation/Energy Datasets	Public mobility, energy, and renewable-related datasets	Travel demand, load profiles, renewable generation, charging infrastructure-related data	Public research data platform	Useful for scenario generation, renewable integration, and uncertainty modeling	Requires careful data cleaning and alignment with optimization time steps	Robust and stochastic optimization, renewable-aware charging, large-scale scenario analysis	[22, 39]
Synthetic EV Fleet Data	Simulated EV charging dataset	Randomly generated arrival times, departure times, initial SoC, required SoC, charging demand	Generated by researchers using statistical distributions	Highly flexible; allows controlled testing across different fleet sizes	May not represent real user behavior accurately	Scalability analysis, sensitivity testing, comparison of solver and heuristic methods	[24, 37]
Real-World TOU/Dynamic Tariff Scenarios	Tariff-based input data	Electricity prices, peak/off-peak periods, demand charges, real-time pricing signals	Utility or market-based tariff data	Supports realistic economic evaluation of charging strategies	Usually does not include EV behavior or grid constraints by itself	Cost saving analysis, off-peak charging, dynamic pricing optimization	[11, 30, 32]
Scenario-Based Uncertainty Data	Generated or sampled uncertainty scenarios	Stochastic arrivals, uncertain charging demand, renewable uncertainty, price uncertainty	Generated from historical data or probability distributions	Useful for robust and stochastic optimization	Results depend strongly on scenario design and probability assumptions	Robust scheduling, stochastic optimization, uncertainty-aware feasibility analysis	[45, 50]

Note: Dataset availability, variables, and preprocessing requirements may differ across studies. In many EV charging optimization papers, standardized grid test systems such as IEEE feeders are combined with synthetic EV charging profiles or real-world tariff data. Therefore, dataset choice directly affects the reported performance of optimization methods, especially in terms of runtime, feasibility, cost reduction, and peak-load reduction

3.1.3 *Comparative analysis of solver-based and non-solver-based approaches*

A comparison of solver-based and non-solver-based approaches shows clear trade-offs in optimality, computational performance, scalability, and modeling flexibility. Heuristic and data-driven methods offer adaptability and speed, but solver-based frameworks particularly those implemented in IBM CPLEX remain the reference standard for producing deterministic and reproducible schedules in complex, constraint-heavy environments.

3.1.3.1 *Solver-based optimization (MILP with CPLEX)*

Solver-based methods, most often formulated as Mixed-Integer Linear Programming (MILP) and implemented in commercial solvers such as IBM CPLEX, provide deterministic optimality guarantees and the ability to rigorously handle technical constraints. One of their key advantages is the robust incorporation of grid-aware limits, including transformer capacity, voltage stability, load balancing, and time-dependent tariffs, all of which are difficult to model accurately with heuristic approaches. These features make solver-based formulations particularly attractive for large-scale EV fleets, where structured mathematical models can exploit problem sparsity and deliver reproducible solutions [7, 29].

Despite these strengths, solver-based optimization is not without drawbacks. In real-time or highly dynamic environments, the computational burden can become prohibitive, particularly when the number of vehicles and stochastic events increases. In addition, solver-based models often require precise parameterization, and their performance can deteriorate when input data such as arrival patterns or user preferences are poorly estimated. This sensitivity limits their applicability in contexts where behavior-driven objectives must be accommodated with flexibility [15]. The literature provides several examples that illustrate both the advantages and challenges of this class of methods. A MILP formulation solved with a commercial solver was shown to reduce peak demand by approximately 12% compared to heuristic baselines, while still preserving transformer capacity limits [7]. Superior convergence rates in grid-constrained scenarios were further reported, showing that solver-based models scale well to distribution networks with hundreds of EVs [29]. Complementing these findings, hybrid models combining MILP with metaheuristic search were shown to retain solver-level optimality while reducing computation time, thereby addressing one of the main limitations of exact methods [15]. Collectively, these studies confirm that solver-based MILP formulations offer a powerful and reliable foundation for EV charging optimization, provided that computational constraints and parameter sensitivities are carefully managed.

3.1.3.2 *Limitations and adoption barriers of commercial solvers*

Although commercial solvers such as IBM CPLEX and Gurobi provide strong advantages in terms of optimality guarantees, constraint handling, and reproducibility, their use in EV charging scheduling is not without limitations. A balanced assessment of solver-based optimization requires consideration of practical barriers that may affect their adoption in real-world applications.

First, commercial licensing cost can limit the accessibility of solvers such as CPLEX, particularly for small research groups, public institutions, and practitioners who require scalable deployment across multiple computing environments. While academic licenses may reduce this barrier in university settings, commercial deployment often requires additional licensing and maintenance costs. This may encourage some researchers and practitioners to prefer open-source solvers or heuristic methods, even when exact optimization would provide stronger guarantees.

Second, memory usage and computational scalability remain important concerns for large MILP formulations. In EV charging scheduling, the number of decision variables increases rapidly with the number of vehicles, charging stations, time intervals, binary charging decisions, and grid constraints. When V2G operation, transformer capacity limits, voltage constraints, and uncertainty scenarios are included simultaneously, the model size can grow substantially. As a result, even if the formulation is mathematically rigorous, solving large-scale MILP models may require significant RAM, long computation times, or advanced decomposition techniques.

Third, solver performance may decrease when the scheduling problem includes nonlinear battery behavior, degradation effects, or detailed electrochemical constraints. Many EV charging studies simplify these aspects to preserve MILP linearity. However, realistic battery degradation, charging efficiency variations, and nonlinear power-flow constraints may lead to

Mixed-Integer Nonlinear Programming (MINLP) or convex/non-convex formulations. These models are generally more difficult to solve than linear MILP models and may reduce the computational advantage of commercial solvers.

Fourth, real-time and online scheduling requirements create additional challenges. In practical charging management systems, new vehicles may arrive unexpectedly, user preferences may change, electricity prices may be updated dynamically, and renewable generation may fluctuate. Under such conditions, the optimization problem must be solved repeatedly within short time intervals. Standard MILP formulations solved by commercial solvers may become computationally expensive for high-frequency updates unless they are combined with rolling-horizon optimization, model predictive control, decomposition, warm-start strategies, or machine-learning-based prediction.

Finally, the reliance on commercial solvers raises reproducibility and accessibility concerns. Although CPLEX and Gurobi are widely used in optimization research, results may depend on solver version, parameter settings, hardware configuration, time limits, and license availability. Therefore, future studies should report solver settings, hardware specifications, runtime limits, optimality gaps, and memory usage in detail. In addition, comparisons with open-source alternatives such as CBC, GLPK, SCIP, or HiGHS would help clarify when commercial solvers are necessary and when open-source tools can provide sufficient performance.

Overall, commercial solvers should not be viewed as universally superior solutions for all EV charging scheduling problems. Rather, they are best understood as rigorous reference tools for constraint-rich and reproducible optimization models. Their practical effectiveness depends on problem size, model linearity, data quality, computational resources, licensing conditions, and the need for real-time responsiveness. Hybrid frameworks that combine commercial solvers with decomposition, heuristic preprocessing, model predictive control, or machine-learning-based forecasting may therefore offer a more realistic pathway for scalable EV charging optimization.

These limitations explain why heuristic, metaheuristic, and hybrid approaches continue to play an important role in EV charging scheduling, especially in large-scale, uncertain, or real-time environments where computational speed and adaptability are critical.

3.1.3.3 *Non-solver methods (heuristics and metaheuristics)*

Heuristic and metaheuristic approaches, such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Ant Colony Optimization (ACO), and Tabu Search, have been widely adopted in EV charging research, particularly in contexts where exact formulations are computationally prohibitive or when modeling flexibility is prioritized. These methods are valued for their fast computation in very large or exploratory instances and their ability to incorporate multi-objective formulations that capture user preferences, waiting times, and other behavior-driven considerations. Unlike solver-based formulations that rely on rigid mathematical models, metaheuristics can flexibly represent qualitative or uncertain factors, making them suitable for scenarios where input data are stochastic or incomplete [24, 25, 45]. For example, a Tabu Search heuristic was compared against CPLEX on standard benchmark datasets and it was shown that while both approaches achieved comparable solution quality, Tabu Search drastically reduced runtime, highlighting its computational efficiency despite lacking guarantees of global optimality [45].

Nevertheless, the limitations of heuristic methods are well documented. Since they lack provable guarantees of global optimality, solutions are often near-optimal and prone to local minima. Their performance can also vary substantially depending on parameter calibration, initial conditions, and search operators, which reduces reproducibility across studies. Moreover, when complex technical constraints such as transformer capacity, voltage stability, or V2G feasibility must be included, these are frequently modeled through penalty terms or custom-encoded rules, which can lead to feasibility violations or overly conservative solutions [51, 52].

Empirical studies illustrate both the strengths and weaknesses of these approaches. PSO was applied for decentralized EV scheduling and achieved satisfactory load balancing; however, the solution incurred 8%–10% higher operational costs compared to solver-based optimization [24]. Similarly, agent-based heuristics were employed in a multi-agent charging system, which improved local coordination among EVs but did not guarantee system-wide feasibility under peak load conditions [25].

Taken together, the empirical evidence indicates that although heuristic and metaheuristic approaches provide computational efficiency and modeling flexibility, they are less reliable for ensuring strict constraint compliance and reproducibility, particularly in large-scale, grid-sensitive contexts.

3.1.3.4 *Hybrid and data-driven methods*

Hybrid frameworks that combine solver-based optimization with predictive models and heuristic techniques have gained traction in recent years for their ability to balance optimality, flexibility, and computational efficiency. These models typically embed Machine Learning (ML) forecasts such as demand clustering or arrival-time prediction into MILP formulations to inform optimization without sacrificing solution quality. For instance, frameworks that integrate centralized MILP scheduling with distributed GA fine-tuning have demonstrated improved load balancing and user satisfaction across multiple stations.

Similarly, hybrid methods based on Model Predictive Control (MPC) augmented with ML forecasting have shown dramatic reductions in both peak load and electricity cost. For example, MPC integrated with predictive models has been applied to optimize EV charging control in a demand-side management context, reducing operational costs while maintaining user satisfaction [53].

These hybrid approaches come with their own modeling complexities. Combining ML, heuristics, and MILP requires expertise in both solver formulation and predictive modeling, and the increased architectural complexity can pose challenges for implementation and scalability. Nevertheless, when effectively designed, these methods can achieve near-global optimality with reduced computation time, adapt to real-time uncertainty, and better accommodate heterogeneous user preferences and stochastic charging behavior. In practice, this versatility makes hybrid and data-driven frameworks highly promising for advancing EV charging optimization in realistic, large-scale deployments.

3.2 *Integration of advanced features*

Real-time Scheduling and Model Predictive Control (MPC): Practical EV management requires real-time flexibility to handle sudden vehicle arrivals and price changes. Model Predictive Control (MPC) solves optimization over a moving window, allowing continuous adjustments. Studies [53] show that MPC, when combined with predictive tools, can significantly reduce operational costs and peak grid stress compared to static and offline methods.

As the field of Electric Vehicle (EV) charging optimization matures, research has increasingly focused on integrating advanced features that bridge the gap between theoretical models and practical implementations. Key elements such as Vehicle-to-Grid (V2G) participation, uncertainty modeling, and user behavior representation play a central role in developing realistic and scalable scheduling frameworks [22, 46].

3.2.1 *Vehicle-to-Grid (V2G) integration*

Vehicle-to-Grid (V2G) technology enables Electric Vehicles (EVs) not only to consume electricity but also to act as distributed energy resources by discharging power back to the grid during peak periods. This bidirectional interaction can enhance grid flexibility, reduce peak demand, and support renewable energy integration by aligning EV charging and discharging cycles with intermittent generation sources such as solar and wind.

Recent studies have examined V2G integration using both solver-based and heuristic approaches. For instance, a mixed-integer programming formulation solved with a commercial solver was proposed, explicitly modeling State-of-Charge (SoC) dynamics, charging and discharging efficiencies, and grid capacity limits [22]. This framework reduced peak demand by nearly 15% compared to unidirectional charging strategies, while maintaining strict grid feasibility. Solver-based formulations are particularly effective in V2G contexts because they can optimize multiple objectives simultaneously, including economic cost, technical feasibility, and energy arbitrage within a unified decision-making structure.

In parallel, heuristic and metaheuristic methods such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) have also been applied to V2G scheduling problems. For example, it was demonstrated that decentralized heuristic decision-making could achieve cost reductions in V2G-enabled fleets [48]. However, these methods often rely on simplified assumptions and may omit detailed grid-network constraints, voltage stability checks, or battery degradation considerations.

As a result, while heuristics provide computational efficiency and adaptability, their applicability for system-level planning and regulatory compliance remains limited.

It was further provided that a comprehensive assessment of the multidimensional impacts of EV and V2G adoption emphasized both the opportunities for enhancing grid stability and renewable integration and the challenges posed by infrastructure limitations, communication requirements, and battery degradation [5]. Their analysis highlights that large-scale deployment of V2G requires not only robust optimization but also regulatory and technological readiness. Taken together, the literature suggests that solver-based optimization provides a more rigorous and scalable foundation for V2G scheduling, particularly when the accurate representation of grid capacity, SoC dynamics, and dynamic pricing signals is critical to ensuring both feasibility and optimality.

3.2.2 *Uncertainty modeling*

EV charging scheduling is inherently exposed to multiple sources of uncertainty, including stochastic vehicle arrivals, volatile electricity prices, and fluctuating renewable generation outputs. If not properly addressed, these uncertainties can lead to significant deviations from planned schedules, resulting in cost overruns or violations of grid constraints. To tackle this challenge, several strands of research have emerged. A moving-horizon MILP framework for real-time EV scheduling on an IEEE 13-node feeder was proposed, which dynamically updated charging decisions as vehicles arrived. The results showed that the approach ensured all vehicles reached the required state-of-charge while maintaining grid feasibility, with average solution times of about 16–17 seconds across 100 scenarios.

Complementing this, robust optimization offers an alternative that emphasizes worst-case performance. A robust MILP formulation was developed that preserved feasibility even under extreme demand and price fluctuations, ensuring reliable operation during grid-stressed conditions and outperforming heuristic counterparts in terms of both feasibility and cost-effectiveness [45]. Extending this line, a two-stage robust optimization model was proposed that jointly integrates EV charging, PV generation uncertainty, battery storage, and demand response under TOU/RTP tariffs. Using a Column-and-Constraint Generation (C&CG) algorithm, the study reported higher resilience and more realistic capacity recommendations compared to deterministic counterparts [34].

Similarly, a two-stage stochastic programming model for locating capacitated EV charging stations under demand uncertainty was proposed. By employing a Benders decomposition–based heuristic, the framework achieved near-optimal solutions with small optimality gaps, demonstrating improved robustness and practical feasibility compared to deterministic siting models [54]. This direction was extended by a two-stage robust optimization framework that jointly integrates EV charging, microgrid compensators, storage, demand response, and renewable variability, solved via C&CG. The results showed improved feasibility and reduced operational costs under high uncertainty [20]. This perspective is consistent with findings that uncoordinated charging at scale can lead to unpredictable voltage imbalances, harmonic distortions, and overloading of distribution assets—effects that further underscore the necessity of robust uncertainty modeling in EV integration [5]. Another promising direction lies in hybrid predictive approaches, such as the work that combined machine learning–based demand forecasting with solver-based scheduling [37]. By generating more accurate scenario inputs, this framework reduced the prevalence of infeasible or suboptimal schedules, thereby improving operational performance and computational efficiency.

Overall, the evidence suggests that embedding stochastic, robust, and predictive methods into solver-based frameworks offers a structured and scalable pathway for addressing uncertainty. In contrast, purely heuristic approaches remain more flexible but often fall short in ensuring feasibility under highly variable conditions.

3.2.3 *User behavior and dynamic pricing*

Modeling user behavior is essential to ensure that optimization outcomes align with real-world adoption patterns, since factors such as departure time preferences, price elasticity, and participation in Demand-Response (DR) programs strongly affect both scheduling effectiveness and user compliance.

Recent studies have demonstrated multiple ways of embedding these aspects into EV charging frameworks. A MILP formulation solved with a commercial solver was developed that integrated user price elasticity into time-of-use tariff schemes. This approach achieved 7%–9% cost savings and alleviated peak-hour congestion by incentivizing off-peak charging behavior, while still maintaining grid feasibility [11]. Agent-based modeling was also explored to capture heterogeneous user preferences and decision-making rules, which proved effective for representing diverse charging behaviors but lacked integration with solver-based optimization, thereby limiting guarantees of system-wide feasibility [55]. More recently, it was shown that combining behavioral forecasting with exact optimization yields more realistic and grid-aware schedules. By embedding user-specific constraints, such as minimum required state-of-charge at departure, directly into MILP formulations, the resulting schedules simultaneously enhanced user satisfaction and preserved technical feasibility [38].

3.2.4 *Additional methodological dimensions for practical deployment*

Beyond V2G integration, uncertainty modeling, and user behavior representation, several additional methodological dimensions are critical for the practical deployment of EV charging scheduling frameworks. These dimensions are often treated only partially in the literature, although they directly affect the reliability, fairness, economic feasibility, and real-time applicability of charging strategies.

First, multi-objective and Pareto-based optimization should be considered more explicitly. EV charging scheduling typically involves conflicting objectives, such as minimizing charging cost, reducing peak demand, limiting battery degradation, improving user satisfaction, and maintaining grid feasibility. Optimizing only a single weighted objective may hide important trade-offs among these goals. Pareto-based methods can provide a set of non-dominated solutions, allowing system operators to evaluate different compromises between economic and technical objectives.

Second, fairness among EV users is an important but underdeveloped aspect of scheduling models. In many optimization frameworks, system-level objectives such as total cost minimization or peak-load reduction may unintentionally prioritize some users over others. For example, users with flexible departure times may receive lower charging priority, or users arriving during congested periods may experience reduced service quality. Fairness-aware formulations can include constraints or penalty terms related to waiting time, charging completion probability, priority classes, or equitable allocation of charging power.

Third, battery degradation modeling is essential in V2G-enabled scheduling. While V2G can provide grid support and economic benefits, frequent charging and discharging cycles may accelerate battery aging. Therefore, scheduling models should account for degradation costs associated with depth of discharge, cycle frequency, charging rate, and battery state of health. Ignoring battery degradation may overestimate the economic attractiveness of V2G and reduce user willingness to participate in bidirectional energy services.

Fourth, charging infrastructure degradation and operational wear should also be considered. High utilization of fast chargers, frequent high-power operation, and thermal stress may increase maintenance requirements and shorten equipment lifetime. Most existing studies focus on vehicle-side battery degradation but overlook charger-side degradation and infrastructure maintenance costs. Incorporating these costs would provide a more realistic assessment of long-term charging station operation and investment planning.

Finally, communication latency and data reliability are critical for real-time and distributed charging control. Practical charging systems depend on communication among EVs, charging stations, aggregators, distribution system operators, and energy markets. Delays, packet losses, forecasting errors, or incomplete information may reduce the effectiveness of centralized or distributed optimization. Therefore, real-time scheduling frameworks should consider latency-aware control, robust communication assumptions, fallback strategies, and rolling-horizon updates.

Overall, these methodological dimensions show that practical EV charging scheduling is not only an optimization problem but also a techno-economic and cyber-physical coordination problem. Future studies should integrate Pareto-based multi-objective optimization, fairness-aware user modeling, battery and infrastructure degradation costs, and communication-aware real-time control into unified frameworks. Such integration would make solver-based, heuristic, and hybrid approaches more suitable for real-world deployment.

Collectively, these studies highlight that embedding user-centric factors within solver-based optimization frameworks significantly increases the practicality of EV charging solutions. Hybrid models that merge behavioral forecasting with mathematical optimization appear particularly promising, as they can balance grid efficiency with user satisfaction and overcome limitations that arise in both purely technical solver models and purely behavioral simulations.

3.3 *Literature gaps*

Despite the considerable progress in Electric Vehicle (EV) charging optimization research, several methodological and practical gaps remain. These gaps limit the operational feasibility of current models and highlight the need for integrated, solver-based frameworks that can connect theoretical modeling with real-world implementation.

3.3.1 *Underutilization of commercial-grade solvers*

Although commercial solvers such as IBM CPLEX have shown high efficiency in solving large-scale, constraint-rich MILP formulations with deterministic precision, their adoption in EV charging literature remains limited [7, 8]. Many studies still favor heuristic or metaheuristic methods [24, 25] that, while faster in computation, do not guarantee global optimality and often fall short in rigorously modeling grid constraints.

Comparative benchmarking between solver-based, heuristic, and hybrid approaches especially regarding scalability, runtime, and solution quality remains scarce. This lack of standardized evaluation protocols underreports the practical advantages of commercial solvers, slowing their broader adoption.

Implication: Establishing standardized solver performance benchmarks would make these advantages more visible and accelerate the adoption of commercial solvers in both research and industry.

3.3.2 *Limited integration of Vehicle-to-Grid (V2G) in solver-based models*

Solver-based models often focus on static charging optimization with limited incorporation of battery degradation costs and dynamic grid interactions [55]. While heuristic approaches can more easily represent V2G flexibility, they tend to oversimplify operational constraints, reducing their value for system-level planning.

Implication: Developing unified, solver-based models that rigorously capture V2G dynamics, both technical and economic, would enable more realistic and actionable optimization outcomes.

3.3.3 *Inadequate treatment of uncertainty*

Most existing studies address uncertainty from stochastic arrivals, dynamic pricing, or renewable variability in isolation, rather than in an integrated manner. Although stochastic MILP and robust optimization studies exist [41, 47], they rarely handle multiple uncertainty sources simultaneously. Recent reviews also emphasize that spatio-temporal coordination under uncertainty remains underexplored, particularly when integrating user demand and renewable variability in a unified framework [28]. Hybrid ML + solver-based approaches are still in their infancy [37].

Implication: Integrating multiple uncertainty sources into solver-based frameworks through combined stochastic and robust techniques would improve model completeness and operational reliability.

3.3.4 *Simplified user behavior modeling*

User-centric elements such as price elasticity, preferred charging times, and participation in demand-response programs are often oversimplified or modeled separately from solver-based optimization [11, 27, 28, 56]. As highlighted in recent studies, current models still tend to neglect user-specific charging patterns and preferences, limiting their applicability in real-world adoption scenarios [27, 28]. As a result, many models achieve mathematical optimality without ensuring realistic adoption rates.

Implication: Embedding behavioral constraints directly into solver formulations would yield solutions that are both technically optimal and aligned with actual user participation patterns.

3.3.5 *Lack of real-world validation*

A large portion of the literature relies on synthetic datasets or small-scale test cases, with limited trials under actual operational conditions [15, 27–29]. In particular, recent studies emphasize that scalability issues, the scarcity of openly available benchmark datasets, and the lack of spatio-temporal validation hinder confidence in deploying solver-based models at scale [27, 28]. For example, the integration of EV chargers into DC trolleygrid systems was analyzed, highlighting the infrastructural and technical complexities of large-scale implementation [55]. The lack of real-world validation undermines the generalizability and industry adoption of many promising approaches.

Implication: Conducting field-scale demonstrations and creating open-access benchmark datasets would strengthen the link between academic models and real-world deployment.

4. Conclusion

4.1 *Future trends*

The evolution of Electric Vehicle (EV) charging optimization will be shaped by growing grid complexity, increasing EV penetration, and advances in computational capabilities. Future research and deployment efforts are expected to focus on the following priority areas:

4.1.1 *Hybrid optimization with machine learning and heuristics*

While solvers like IBM CPLEX deliver rigorous optimality guarantees, their computational requirements can be restrictive for real-time applications. Future frameworks will increasingly combine MILP-based solvers with Machine Learning (ML) forecasting and heuristic preprocessing. ML models can predict demand and narrow feasible solution spaces, which are then refined by the solver for optimality [15, 37].

Expected Outcome: Significant reduction in computation time without sacrificing solution quality, enabling near real-time scheduling for large-scale EV networks.

4.1.2 *V2G-Centric and uncertainty-resilient optimization*

As Vehicle-to-Grid (V2G) technology becomes commercially viable, optimization models are expected to incorporate bidirectional energy flows, battery degradation costs, and energy arbitrage opportunities. At the same time, multi-scenario uncertainty modeling that captures stochastic vehicle arrivals, dynamic pricing, and renewable generation variability will increasingly be integrated into solver-based frameworks through stochastic and robust optimization methods [22, 46, 47]. In this way, future approaches are likely to generate flexible and resilient charging schedules that enhance grid stability while simultaneously maximizing economic returns under diverse and changing operating conditions.

4.1.3 *User behavior-aware scheduling*

Future models will embed behavioral economics and participation modeling directly into solver formulations, integrating factors such as price elasticity, preferred charging times, and Demand-Response (DR) program participation rates [11, 55]. Agent-based simulations may also be combined with solver-based optimization to better capture heterogeneous user behavior, predict adoption patterns, and improve compliance. In this way, upcoming approaches are expected to achieve greater user participation, stronger alignment between optimization outcomes and real-world behavior, and ultimately higher adoption of coordinated charging programs.

4.1.4 *Scalable solver deployment via HPC and digital twins*

To handle rapidly growing problem sizes, future solver-based frameworks will increasingly rely on High-Performance Computing (HPC), parallelized solvers, and cloud-based platforms [8, 15]. At the same time, digital twin technology, which refers to virtual replicas of distribution grids, will be integrated to allow realistic testing and validation of charging strategies before large-scale deployment [21, 29]. Through these advancements, solver-based approaches are expected to achieve industrial-grade scalability with low operational risk, thereby enabling real-time, city-scale EV charging coordination.

4.2 *Overall conclusion*

The scientific originality of this review lies in its systematic and numerical benchmarking of commercial solver-based optimization against heuristic and data-driven alternatives, an analysis that was previously fragmented in the literature. By synthesizing quantitative performance metrics, such as optimality gaps and computational runtimes across standardized datasets, this study provides a concrete framework that bridges the gap between theoretical mathematical models and practical, scalable deployment strategies for EV charging infrastructure.

Optimizing Electric Vehicle (EV) charging schedules has become a central research challenge at the intersection of transportation electrification and smart grid development. This review compared solver-based, heuristic, and data-driven methods, highlighting their respective strengths, weaknesses, and areas of application.

The evidence shows clear advantages for solver-based optimization, particularly MILP models implemented with commercial solvers such as IBM CPLEX. These approaches deliver guaranteed optimal solutions and handle grid constraints effectively, though their computational demands remain a barrier for very large systems [7, 8, 15]. By contrast, heuristic and metaheuristic methods are faster but often fall short in reproducibility and constraint compliance [24, 25].

Several research gaps remain. Key areas include the integration of grid-level constraints, the modeling of user behavior, multi-source uncertainty, and the creation of standardized benchmarks for solver performance. Without these, scalability and operational reliability remain limited.

Future work can address these challenges through hybrid frameworks that combine solver-based optimization with machine learning or heuristic preprocessing, enabling faster computation without losing solution quality. Greater emphasis on V2G-aware and uncertainty-resilient scheduling will strengthen grid flexibility and economic outcomes. Incorporating user behavior into optimization frameworks will also improve adoption and ensure realistic results. Advances in High-Performance Computing (HPC) and digital twins are likely to push solver-based approaches toward real-time, city-scale deployment. Positioning solver-based methods, particularly CPLEX, as a standard reference can help bridge the gap between academic models and industry practice. Embedding these solvers into hybrid and scalable frameworks offers the prospect of solutions that are both technically reliable and cost-effective.

Author contributions

V.T.: Conceptualization, Literature review, Methodology, Writing—original draft preparation. A.M.V.: Supervision, Methodology, Validation, Writing—reviewing and editing.

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Conflicts of interest

The authors declare no conflicts of interest.

Abbreviation

IBM CPLEX	IBM ILOG CPLEX Optimization Studio
PV	Photovoltaic
PCA	Principal Component Analysis
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SoC	State of Charge
ACO	Ant Colony Optimization
EVRPTW	Electric Vehicle Routing Problem with Time Windows
MIP	Mixed-Integer Programming
CP	Constraint Programming
MIQCP	Mixed-Integer Quadratically Constrained Programming
TOU	Time-of-Use
RTP	Real-Time Pricing
SSA	Salp Swarm Algorithm
AOA	Arithmetic Optimization Algorithm
RMSE	Root Mean Square Error
IoT	Internet of Things
RL	Reinforcement Learning
GAMS	General Algebraic Modeling System
LP	Linear Programming
MIQP	Mixed-Integer Quadratic Programming
NR	Not Reported
QP	Quadratic Programming
ACN	Adaptive Charging Network
ACN-Sim	Adaptive Charging Network Simulator
JPL	Jet Propulsion Laboratory
NREL	National Renewable Energy Laboratory
PEV	Plug-in Electric Vehicle
IEEE	Institute of Electrical and Electronics Engineers
RAM	Random-Access Memory
CBC	COIN-OR Branch-and-Cut
GLPK	GNU Linear Programming Kit
SCIP	Solving Constraint Integer Programs
HiGHS	High-performance parallel linear optimization software

References

[1] International Energy Agency, "Global EV Outlook 2023: Catching up with climate ambitions," 2023. [online]. Available: https://www.iea.org/reports/global-ev-outlook-2023. [Accessed May 2, 2026].

[2] BloombergNEF, "Electric Vehicle Outlook 2026," 2026. [online]. Available https://about.bnef.com/electric-vehicle-outlook/. [Accessed May 12, 2026].

[3] H. J. Khasawneh and H. Hussein, "Jordan's electric vehicle growth drives trade-offs," *Science*, vol. 387, no. 6735, pp. 726, 2025. https://doi.org/10.1126/science.adu1313.

[4] M. Belaid, S. El Beid, S. Doubabi, and A. Hatim, "Planning and optimizing charging infrastructure and scheduling in smart grids with PyPSA-LOPF: A case study at Cadi Ayyad University," *World Electric Vehicle Journal*, vol. 16, no. 5, p. 278, 2025. https://doi.org/10.3390/wevj16050278.

[5] R. A. Ibrahim, I. M. Gaber, and N. E. Zakzouk, "Analysis of multidimensional impacts of electric vehicles penetration in distribution networks," *Scientific Reports*, vol. 14, p. 27854, 2024. https://doi.org/10.1038/s41598-024-77662-6.

[6] J. A. Guerrero-Silva, J. I. Romero-Gelvez, A. J. Aristizábal, and S. Zapata, "Optimization and trends in EV charging infrastructure: A PCA-based systematic review," *World Electric Vehicle Journal*, vol. 16, no. 7, p. 345, 2025. https://doi.org/10.3390/wevj16070345.

[7] S. Sabzi and L. Vajta, "Optimizing electric vehicle charging considering driver satisfaction with market integration," In Proc. 2024 9th International Youth Conference on Energy (IYCE), Colmar, France, Jul. 2-4, 2024, pp. 1-6. https://doi.org/10.1109/IYCE60333.2024.10634927.

[8] U. Chawal, J. Rosenberger, V. C. P. Chen, W. J. Lee, M. Wijemanne, R. K. Punugua, and A. Kulvanitchaiyanunt, "Optimizing a system of electric vehicle charging stations using mixed integer linear programming computer experiments," *SSRN Electronic Journal*, 2023. https://doi.org/10.2139/ssrn.4572175.

[9] W. Ma and X. Fang, "Multi-agent deep reinforcement learning for EV charging coordination," 2021. [online]. Available: https://arxiv.org/abs/2112.04221. [Accessed May 12, 2026].

[10] C. Yao, S. Chen, and Z. Yang, "Joint routing and charging problem of multiple electric vehicles: A fast optimization algorithm," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 8184-8195, 2022. https://doi.org/10.1109/TITS.2021.3076601.

[11] A. Almutairi and T. M. Aljohani, "Reliability-driven time-of-use tariffs for efficient plug-in electric vehicle integration," *Sustainable Cities and Society*, vol. 107, p. 105463, 2024. https://doi.org/10.1016/j.scs.2024.105463.

[12] W. Sun, F. Neumann, and G. P. Harrison, "Robust scheduling of electric vehicle charging in LV distribution networks under uncertainty," *IEEE Transactions on Industry Applications*, vol. 56, no. 5, pp. 5785-5794, 2020. https://doi.org/10.1109/TIA.2020.2983906.

[13] O. Sundström and C. Binding, "Optimization methods to plan the charging of electric vehicle fleets," *ACEEE International Journal on Communication*, vol. 1, no. 2, pp. 45-50, 2010.

[14] S. He, Z. Zhang, S. Han, L. Pepin, G Wang, D. Zhang, et al., "Data-driven distributionally robust electric vehicle balancing for autonomous mobility-on-demand systems under demand and supply uncertainties," 2022. [online]. Available: https://arxiv.org/abs/2211.13797. [Accessed May 12, 2026].

[15] M. Veisi, H. Naderian, and M. Karimi, "Optimal charging station placement of electric vehicles in the smart distribution network based on mixed integer linear programming," *International Journal of Electrical Power & Energy Systems*, vol. 168, p. 110675, 2025. https://doi.org/10.1016/j.ijepes.2025.110675.

[16] M. Kang, B. Lee, and Y. Lee, "A robust optimization approach for e-bus charging and discharging scheduling with vehicle-to-grid integration," *Mathematics*, vol. 13, no. 9, p. 1380, 2025. https://doi.org/10.3390/math13091380.

[17] E. Jonuzi, T. Alkan, S. S. Durduran, and H. Z. Selvi, "Using GIS-supported MCDA method for appropriate site selection of parking lots: The case study of the city of Tetovo, North Macedonia," *International Journal of Engineering and Geosciences*, vol. 9, no. 1, pp. 86-98, 2024. https://doi.org/10.26833/ijeg.1319605.

[18] E. Sert, N. Osmanlı, R. Eruc, and M. Uyan, "Determination of transportation networks based on the optimal public transportation policy using spatial and network analysis methods: A case of Konya, Turkey," *International Journal of Engineering and Geosciences*, vol. 2, no. 1, pp. 27-34, 2017. https://doi.org/10.26833/ijeg.286034.

[19] V. Adjiski, G. Kaplan, and S. Mijalkovski, "Assessment of the solar energy potential of rooftops using LiDAR datasets and GIS based approach," *International Journal of Engineering and Geosciences*, vol. 8, no. 2, pp. 188-199, 2023. https://doi.org/10.26833/ijeg.1112274.

[20] B. Kartal and R. M. Alkan, "Solar energy based model for decarbonization: A case study in Istanbul," *International Journal of Engineering and Geosciences*, vol. 11, no. 1, pp. 64-77, 2025. https://doi.org/10.26833/ijeg.1648588.

[21] X. Zhao and G. Liang, "Optimizing electric vehicle charging schedules and energy management in smart grids using an integrated GA-GRU-RL approach," *Frontiers in Energy Research*, vol. 11, p. 1268513, 2023. https://doi.org/10.3389/fenrg.2023.1268513.

[22] H. Hematian, M. T. Askari, M. A. Ahmadi, M. Sameemoqadam, and M. Babaei Nik, "Robust optimization for microgrid management with compensator, EV, storage, demand response, and renewable integration," *IEEE Access*, vol. 12, pp. 73413-73425, 2024. https://doi.org/10.1109/ACCESS.2024.3401834.

[23] A. Erener and A. Şirin, "Python-based evaluation of road network constraints for electric scooters and bicycles: Izmit example," *International Journal of Engineering and Geosciences*, vol. 9, no. 1, pp. 34-48, 2024. https://doi.org/10.26833/ijeg.1261677.

[24] A. Azerine, A. Oulamara, I. Zaidi, A. Khodja, and L. Idoumghar, "Energy maximization for electric vehicle charging scheduling: Meta-heuristic approaches," In Proc. 2024 10th International Conference on Control, Decision and

Information Technologies (CoDIT), Vallette, Malta, Jul. 1-4, 2024, pp. 1-6. https://doi.org/10.1109/CoDIT62066.2024.10708620.
[25] P. Plagowski, A. Saprykin, N. Chokani, and R. Shokrollah-Abhari, "Impact of electric vehicle charging—an agent-based approach," *IET Generation, Transmission & Distribution*, vol. 15, no. 18, pp. 2605-2617, 2021. https://doi.org/10.1049/gtd2.12202.
[26] S. S. A. Salam, V. Raj, M. I. Petra; A. K. Azad, S. Mathew, and S. M. Sulthan, "Charge scheduling optimization of electric vehicles: A comprehensive review of essentiality, perspectives, techniques, and security," *IEEE Access*, vol. 12, pp. 121010-121030, 2024. https://doi.org/10.1109/ACCESS.2024.3433031.
[27] H. M. Al-Alwash, E. Borcoci, M.-C. Vochin, I. A. M. Balapuwaduge, and F. Y. Li, "Optimization schedule schemes for charging electric vehicles: Overview, challenges, and solutions," *IEEE Access*, vol. 12, pp. 32801-32820, 2024. https://doi.org/10.1109/ACCESS.2024.3371890.
[28] E. Elghanam, A. Abdelfatah, M. S. Hassan, and A. H. Osman, "Optimization techniques in electric vehicle charging scheduling, routing and spatio-temporal demand coordination: A systematic review," *IEEE Open Journal of Vehicular Technology*, vol. 5, pp. 1294-1313, 2024. https://doi.org/10.1109/OJVT.2024.3420244.
[29] S. P. Karthikeyan and P. Thomas, "Optimization strategies for electric vehicle charging and routing: A comprehensive review," *Gazi University Journal of Science*, vol. 37, no. 3, pp. 1256-1285, 2024. https://doi.org/10.35378/gujs.1321572.
[30] Maigha and M. L. Crow, "Cost-constrained dynamic optimal electric vehicle charging," *IEEE Transactions on Sustainable Energy*, vol. 8, no. 2, pp. 716-724, 2017. https://doi.org/10.1109/TSTE.2016.2615865.
[31] T. Chen, B. Zhang, H. Pourbabak, A. Kavousi-Fard, and W. Su, "Optimal routing and charging of an electric vehicle fleet for high-efficiency dynamic transit systems," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3563-3572, 2018. https://doi.org/10.1109/TSG.2016.2635025.
[32] A. Ham and M.-J. Park, "Electric vehicle route optimization under time-of-use electricity pricing," *IEEE Access*, vol. 9, pp. 37220-37228, 2021. https://doi.org/10.1109/ACCESS.2021.3063316.
[33] H. Hematian, M. T. Askari, M. A. Ahmadi, M. Sameemoqadam, and M. Babaei Nik, "Robust optimization for microgrid management with compensator, EV, storage, demand response, and renewable integration," *IEEE Access*, vol. 12, pp. 73413-73425, 2024. https://doi.org/10.1109/ACCESS.2024.3401834.
[34] H. Karimianfard, "A robust optimization framework for smart home energy management: Integrating photovoltaic storage, electric vehicle charging, and demand response," *Journal of Energy Storage*, vol. 110, p. 115259, 2025. https://doi.org/10.1016/j.est.2024.115259.
[35] P. Antarasee, S. Premrudeepreechacharn, A. Siritaratiwat, and S. Khunkitti, "Optimal design of electric vehicle fast-charging station's structure using metaheuristic algorithms," *Sustainability*, vol. 15, no. 1, p. 771, 2023. https://doi.org/10.3390/su15010771.
[36] W. Lin, H. Wei, L. Yang, and X. Zhao, "Technical review of electric vehicle charging distribution models with considering driver behaviors impacts," *Journal of Traffic and Transportation Engineering (English Edition)*, vol. 11, no. 4, pp. 643-666, 2024. https://doi.org/10.1016/j.jtte.2024.06.001.
[37] Z. J. Lee, G. Lee, T. Lee, C. Jin, R. Lee, Z. Low, D. Chang, et al., "Adaptive charging networks: A framework for smart electric vehicle charging," 2020. [online]. Available: https://arxiv.org/abs/2012.02636. [Accessed May 12, 2026].
[38] N. Nimalsiri, C. Mediwaththe, E. L. Ratnam, and M. E. Shaw, "A survey of algorithms for distributed charging control of electric vehicles in smart grid," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 11, pp. 4497-4512, 2020. https://doi.org/10.1109/TITS.2019.2943620.
[39] T. D. Tran, N. D. Nguyen, H. T. M. Chu, L. El Ghaoui, L. Ambrosino, and G. Calafiore, "A robust optimization model for cost-efficient and fast electric vehicle charging with L2-norm uncertainty," 2025. [online]. Available https://arxiv.org/abs/2502.04024. [Accessed May 1, 2026].
[40] W. Xu, C. Zhang, M. Cheng, and Y. Huang, "Electric vehicle routing problem with simultaneous pickup and delivery: Mathematical modeling and adaptive large neighborhood search heuristic method," *Energies*, vol. 15, no. 23, p. 9222, 2022. https://doi.org/10.3390/en15239222.
[41] O. Sundström and C. Binding, "Planning electric-drive vehicle charging under constrained grid conditions," In Proc. 2010 International Conference on Power System Technology (POWERCON), Zhejiang, China, Oct. 24-28, 2010, pp. 1-8. https://doi.org/10.1109/POWERCON.2010.5666620.

[42] B. Al-Hanahi, I. Ahmad, D. Habibi, P. Pradhan, and M. A. S. Masoum, "An optimal charging solution for commercial electric vehicles," *IEEE Access*, vol. 10, pp. 46162-46175, 2022. https://doi.org/10.1109/ACCESS.2022.3171048.

[43] Q. Wang, S. Peng, and S. Liu, "Optimization of electric vehicle routing problem using Tabu Search," In Proc. 2020 Chinese Control and Decision Conference (CCDC), Hefei, China, Aug. 22-24, 2020, pp. 2219-2224. https://doi.org/10.1109/CCDC49329.2020.9164769.

[44] H. Li, Z. Li, L. Cao, R. Wang, and M. Ren, "Research on optimization of electric vehicle routing problem with time window," *IEEE Access*, vol. 8, pp. 146707-146718, 2020. https://doi.org/10.1109/ACCESS.2020.3014638.

[45] Z. Wang, F. Zheng, and M. Liu, "Charging scheduling of electric vehicles considering uncertain arrival times and time-of-use price," *Sustainability*, vol. 17, no. 3, p. 1100, 2025. https://doi.org/10.3390/su17031100.

[46] L. Zhang, C. Sun, G. Cai, and L. H. Koh, "Charging and discharging optimization strategy for electric vehicles considering elasticity demand response," *eTransportation*, vol. 18, p. 100262, 2023. https://doi.org/10.1016/j.etran.2023.100262.

[47] P. Xu, H. Zhao, Y. Chen, and J. Li, "Vehicle charging dispatch integrated with distributed PV, wind, storage, and ML forecasting," *Energy Informatics*, vol. 8, no. 1, pp. 47-62, 2025. https://doi.org/10.1186/s42162-025-00476-x.

[48] Y. Ran, H. Liao, H. Liang, L. Lu, and J. Zhong, "Optimal scheduling strategies for EV charging and discharging in a coupled power-transportation network with V2G scheduling and dynamic pricing," *Energies*, vol. 17, no. 23, p. 6167, 2024. https://doi.org/10.3390/en17236167.

[49] Z. J. Lee, S. Sharma, D. Johansson, and S. H. Low, "ACN-Sim: An open-source simulator for data-driven electric vehicle charging research," 2020. [online]. Available: https://arxiv.org/abs/2012.02809. [Accessed May 12, 2026].

[50] Z. Wang, P. Jochem, and W. Fichtner, "A scenario-based stochastic optimization model for charging scheduling of electric vehicles under uncertainties of vehicle availability and charging demand," *Journal of Cleaner Production*, vol. 254, p. 119886, 2020. https://doi.org/10.1016/j.jclepro.2019.119886.

[51] C. Blum and A. Roli, "Metaheuristics in combinatorial optimization: Overview and conceptual comparison," *ACM Computing Surveys*, vol. 35, no. 3, pp. 268-308, 2003. https://doi.org/10.1145/937503.937505.

[52] E.-G. Talbi, *Metaheuristics: From Design to Implementation*. Hoboken, NJ, USA: John Wiley & Sons, 2009. https://doi.org/10.1002/9780470496916.

[53] V. Fernandez and V. Pérez, "Optimization of electric vehicle charging control in a demand-side management context: A model predictive control approach," *Applied Sciences*, vol. 14, no. 19, p. 8736, 2024. https://doi.org/10.3390/app14198736.

[54] S. A. MirHassani, A. Khaleghi, and F. Hooshmand, "Two-stage stochastic programming model to locate capacitated EV-charging stations in urban areas under demand uncertainty," *EURO Journal on Transportation and Logistics*, vol. 9, no. 1, p. 100025, 2020. https://doi.org/10.1016/j.ejtl.2020.100025.

[55] K. van der Horst, I. Diab, G. R. Chandra Mouli, and P. Bauer, "Methods for increasing the potential of integration of EV chargers into the DC catenary of electric transport grids: A trolleygrid case study," *eTransportation*, vol. 17, p. 100271, 2023. https://doi.org/10.1016/j.etran.2023.100271.

[56] H. I. Shaheen, G. I. Rashed, B. Yang, and J. Yang, "Optimal electric vehicle charging and discharging scheduling using metaheuristic algorithms: V2G approach for cost reduction and grid support," *Journal of Energy Storage*, vol. 90, p. 111816, 2024. https://doi.org/10.1016/j.est.2024.111816.