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Energy-Aware EV Charging Optimization: A SWOT-Informed Hybrid Decision Framework

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Abstract. The increasing of electrical vehicles (EVs) becomes a big challenge for charging infrastructures, including efficiency, grid impact and service quality. To address this need for EV charging management we used methods such as Optimisation, metaheuristics and deep reinforcement learning (DRL), but each method is limited when used separately. This paper proposes a hybrid decision framework guided by a SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis, which provides a structured way to combine and organize these approaches under different operating conditions. To organize the decision-making of this framework we are based on three complementary layers : deterministic optimization for day-ahead planning and constraint satisfaction, metaheuristic tuning for multi-objective trade-offs, and DRL-based control for real-time adaptation under uncertainty. The proposed framework is validated using real-world charging session data from the Adaptive Charging Network (ACN-Data) collected at the Caltech site from March-April 2019, under a constrained site with a 50-kW total limit and 7.2 kW per-charger limit. Under nominal conditions, FCFS, MILP, and MILP+PSO all reach a 1.00 satisfaction rate with 0.0 kWh energy deficit. Under surprise-arrival demand shocks, DRL remains robust: at 50% extra arrivals it achieves 0.937 satisfaction with 2.366 kWh deficit, whereas FCFS drops to 0.835 satisfaction with 45.680 kWh deficit; across 20–50% shocks, DRL reduces unmet energy demand by up to ~95% versus FCFS.

Introduction

The world knows an increase in EVs, and this creates new operational constraints and challenges for the power systems, basically at the distribution level. Except long charging times, uncoordinated or bad charging optimization can provide a lot of issues such as peak demand, increase feeder loading, and make voltage instable, all these factors can create a risk on all grid reliability [1]. One of the key goals for sustainable mobility is to focus on efficient charging that respects the grid and reduces energy waste. This problem focuses on three main parameters : power systems, optimization, and smart control. The methods used must ensure that most user needs are achievable, at the same time should respect the grid limits and adapt to grid conditions across different cases. In research communities, many methods have been proposed to tackle this problem. Mathematical optimization, such as convex programming and Mixed- Integer Linear Programming (MILP) [2], can deliver exact and robust solutions, but when the problem becomes large their scalability is limited. Metaheuristics such as Particle Swarm Optimization (PSO) [3], Genetic Algorithms (GA) [4], and related bio-inspired methods are most used when the problem is complex and has multi-objective parameters, but their convergence is not at the good level, and

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their tuning parameters are usually sensitive and require careful verification. The DRL method [5] has been applied to scheduling in real-time when the parameters of environments are uncertain. However, it mostly requires a lot of data, expensive to run, and is difficult to interpret and validate in critical grid applications. Overall, each family of methods has strengths, but no single approach covers all aspects of EV charging optimization. A clear way is therefore needed to compare these approaches, identify their complementarities, and guide the design of hybrid solutions. To handle all these issues, the SWOT analysis [6] is proposed. It's not limited to listing pros and cons, but it also highlights how the strengths can be combined and weaknesses reduced. This paper makes three main contributions; First, it provides a clear overview of the three methods or approaches used for EV charging. Second, these methods are compared using a SWOT analysis in terms of strengths, weaknesses, opportunities, and threats. Based on their analysis, a conceptual hybrid framework is proposed to use their robust points and integrate them in the different layers and improve EV charging performance. The rest of the paper is organized as follows: Section II reviews related work; Section III presents the SWOT analysis; Section IV describes the framework; and Section V reports the experimental validation and discusses the results; and Section VI concludes the paper.

Literature Review

The research on EV charging optimization is generally classified into three main categories : mathematical optimization, metaheuristic algorithms, and ML methods, with a focus on DRL in recent papers. Each category from the methods listed below has its strengths and weaknesses, which indicate the importance of using a structured comparaison. First, Mathematical optimization methods [1–2, 7–10], such as convex programming and MILP, are applied to deliver exact and robust solutions for small to medium-sized systems. By contrast, when the system grows the computational cost increases, which impact these methods and leads them to be less practical, and especially for large distribution networks with high uncertainty and more variability. Second, metaheuristic methods [3–4, 11–15], that includes GA and PSO, it provides flexible search capabilities for nonlinear or multi-objective formulations and help in scalability performance. However, these approaches can converge slowly, and get stuck in local minima, and are usually sensitive to parameter settings. The new variants and hybrid metaheuristics like; GA-PSO or combinations with simulated annealing (SA), focus on reducing these issues, but its performance depends on different cases. Finally, ML and DRL approches [5, 16–21], have become the most popular due to its adaptability to changing conditions in uncertainty. DRL activates the real-time decision-making and has been integrated with other architectures, specifically, the Graph Neural Networks (GNNs) to handle large fleets. In contrast, these methods require a lot of training data, large computing power, and in most cases, they provide a limited interpretability. All these reasons make their application a little hard and creates a real challenge in smart-grid applications. The literature discussed decentralized coordination, Vehicle-to-Grid (V2G) integration, and scheduling that is fair. In conclusion, DRL can scale to large systems but is highly dependent on data and computational resources; metaheuristics scale better but may have convergence and tuning problems; and mathematical optimization offers optimality guarantees but does not scale well.

The various requirements of EV charging optimization cannot be fully satisfied by a single strategy. The SWOT analysis is presented in the following section to emphasize complementarities and offer a framework for integrating approaches. Common EV charging models like rolling-horizon control, queue-aware scheduling, and grid-constrained optimization are also covered in this review [3, 5, 11]. These models are the basis for the hybrid framework presented in this paper.

SWOT-Based Comparative Analysis

A SWOT analysis is applied to compare the three families of approaches in a clear way. This framework reports the main features of each method, and shows how they can complement each other in hybrid solutions. The results are summarized in Table 1, which presents the SWOT matrix for the three families. For traceability, supporting references are listed for each SWOT category: Optimization [1, 7, 9], Metaheuristics [3, 12, 14, 15], and DRL [5, 18–21].

Table 1. *SWOT analysis of EV charging optimization approaches.*

Approach	Strengths	Weaknesses	Opportunities	Threats
Mathematical Optimization	Exact and robust solutions; strong theoretical guarantees; well-suited for small/medium systems	Poor scalability; exponential computational growth; limited flexibility in dynamic contexts	Can be coupled with heuristics for decomposition; integration into short-term local scheduling	Combinatorial explosion in large-scale systems; sensitivity to uncertainty
Metaheuristics	Flexible and adaptable to complex, multi-objective problems; easy to extend to new scenarios	Slow convergence; risk of local minima; high sensitivity to parameter settings	Well-suited for large-scale and non-convex problems; potential to complement exact or learning-based methods	Highly variable performance; difficulty in ensuring reproducibility
ML/ DRL	Adaptive learning in dynamic environments; scalable with advanced models (e.g., GNNs); potential for real-time scheduling	Data-hungry; computationally expensive; “black box” nature limits interpretability	Promising for smart grids, V2G, and demand-response integration; ability to generalize across scenarios	Computational overhead may limit adoption; trust and transparency issues in critical infrastructure

As described in the previous table presenting the key strengths and weaknesses of each method based on SWOT approach, it is clearly mentioned that no complete Approach encompassing the majority or all pillars of EV charging optimization. Similar solutions with strong foundational guarantees can be provided by mathematical optimization, While it underlines a lack of scalability. Another approach using metaheuristics is limited for its convergence slowness even if it's considered flexible for multi-objectives and complex problems, while the results can be different from one case to another. On the other hand, DRL are much better since they can scale and adapt in a better way, most likely when attached with advanced models like GNNs. However, important computational efforts required with lesser and limited interpretability, thing that makes it a major concern in smart-grid applications. To sum up, each one of those categories has its strengths, and the weakness can be reduced by combining different methods. This highlights the relevant of the

conceptual framework offered in the next section, where the SWOT methodology is used to guide the design of integrated hybrid solutions.

Conceptual Framework

A conceptual framework is proposed, to reduce EV charging time using hybrid algorithms based on the outcomes of SWOT analysis. The idea is to combine all the strengths points of different methods, and reducing their weaknesses, and exploit available opportunities, while limiting the risks. This approach aims to integrate all in one efficient solution. It does not provide a step-by-step procedure to optimize EV charging time. Instead, it is a general design that can be adapted to different scenarios and future implementations.

A. Design Principles

The framework follows three key design principles. First, it builds on the strengths of the three methods proposed in this paper. Mathematical optimization is applied to exact short-term scheduling and feasibility checks. Metaheuristics address multi-objective trade-offs in complex settings, while DRL is used for long-term decisions that must be adapted under uncertainty. Second, the framework reduces the risks of individual methods by combining a DRL with simple heuristics to accelerate learning and reduce the risk of getting stuck in local minima. Large optimization problems are decomposed into smaller, easier sub-problems. Hybrid combinations such as optimization combined with learning or heuristics, are used to limit computational complexity. Finally, the framework exploits available opportunities and control potential risks, by including Smart-grid features such as V2G, demand response, and renewable energy. Computational limits are addressed with distributed computing and cloud–edge setups. Model transparency is improved by adding interpretable parts to data driven methods.

B. Hybrid Workflow

The proposed framework is organized into three layers, each linked to a specific planning horizon. At the short-term level, local optimization is performed using mathematical methods, such as MILP or convex programming, to produce exact charging schedules that respect immediate grid and tariff constraints. For medium-term planning, the framework relies on metaheuristic approches, including PSO and GA, to handle multi-objective trade-offs and support flexible day-ahead or week-ahead planning. Long-term policy adaptation is handled through DRL. In this layer, DRL agents are trained to learn adaptive strategies that work much better across different scenarios, enabling the system to make robust decisions under changing conditions, such as uncertain demand and variable renewable generation.

In this framework, “charging time” means the total time from plug-in until the target state of charge (SoC) is reached. It includes both waiting and active charging times.

Formally, the goal is to minimize the total time a vehicle stays in the station:

$$\min_{P_{i,t}} T_{sojourn} = T_{wait} + T_{charge} \qquad (1)$$

this is done while respecting grid voltage limits, and feeder capacity and tariff constraints :

$$V_{min} \leq V_t \leq V_{max} \qquad (2)$$

The medium-term metaheuristic layer optimizes the multi-objective vector :

$$\left[F = T_{avg}, C_{energy}, R_{peak}\right] \qquad (3)$$

which includes average charging time, energy cost, and peak-load ratio. The long-term DRL layer learns adaptive policies :

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$$\pi(S_t) \rightarrow a_t \qquad (4)$$

using state variables such as SoC distributions, queue lengths, and time-varying prices.

The information shared between the layers includes feasible schedules, heuristic guidance, and the learned parameters of the policy. This maintains consistency in decisions made and scalability across the different time horizons.

C. Conceptual Diagram

To illustrate the workflow described above, Fig. 1 presents a schematic diagram of the proposed framework. The diagram has four layers :

- **Input layer:** EV fleet demand, charging requirements, grid constraints, electricity price signals, and renewable generation profiles.
- **SWOT-guided decision layer:** A central block showing how SWOT categories guide the selection of algorithm families (optimization, metaheuristics, DRL).
- **Hybrid integration layer:** Three connected modules for short-term optimization, medium-term planning, and long-term DRL learning.
- **Output layer:** Optimized charging schedules, reduced charging time, lower costs, and improved grid stability.

The figure provides a visual summary of the hybrid workflow, connecting the SWOT-based analysis (Section 3) to the proposed conceptual framework.

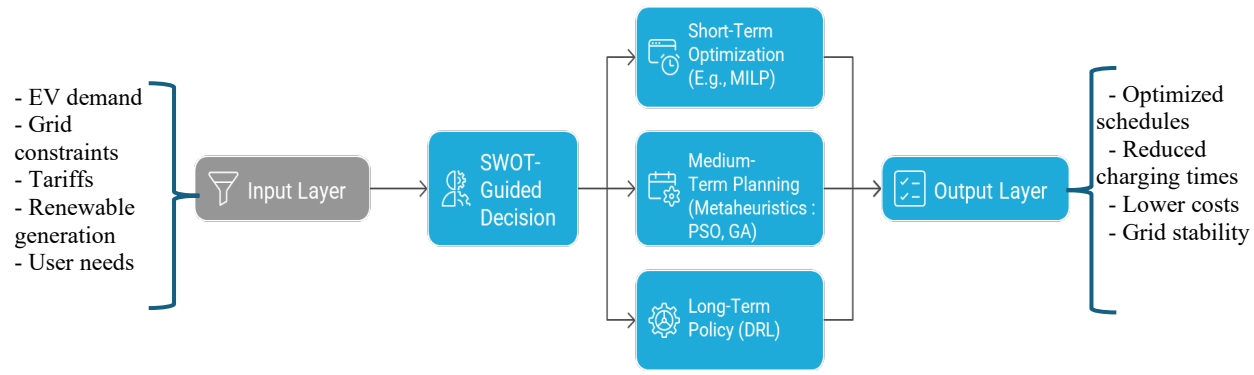


Fig. 1. *Conceptual framework for EV charging optimization guided by SWOT*

D. Advantages of the Proposed Framework

In comparaison with single method approaches that aim to optimize one objectif, the proposed framework is more efficient and has several advantages such as: Robustness, due to its combination of solution quality, flexibility, and adaptability. Scalability and simplicity to apply in large systems due to its decomposition and hybrid design. Adaptability, because the DRL method is flexible in dynamic and uncertain conditions. Over that, it's also practically relevant because SWOT provides a clear way to compare methods and guide how they are combined. The experimental validation is based on four essential metrics: including service satisfaction, energy deficit, peak demand, and energy cost. These metrics are extracted from the objectives and constraints defined in the equations above (1)–(4).

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Experimental Validation and Results

A. Dataset and Experimental Setup

To validate the SWOT-guided hybrid optimization framework, a real EV charging data from the CAN-Data dataset has been used. This dataset includes different charging sessions with its specific arrival and departure times, and the requested energey per vehicle. These charging sessions are collected especially during the period from March-April 2019, to cover the normal weekdays and the extreme demand periods. Each day is handled as a separate scheduling case, and the charging site has a total power limit of 50 kW and a per-charger limit of 7.2 kW.

The time-of-use (TOU), electricity price signal, is applied to evaluate the realistic energy cost variations during the day. To correctly measure the energy not delivered at departure time per vehicle, the simulation time is enlarged by 24 hours when necessary to cover charging sessions that continue past midnight. This ensures accurate calculation of service satisfaction and energy deficit. The energy deficit is defined as the amount of requested energy that is not delivered at vehicle departure, which directly reflects service failure from the user perspective.

B. Scenario 1: Nominal Operation (Predictable Demand)

The framework is evaluated under nominal operating conditions, where arrival and departure times are known and no unexpected events occur. Under these conditions, the planning assumptions are valid, and system stress remains limited.

Three approaches are considered:

- **FCFS** (First-Come First-Served) as a simple heuristic baseline,
- **MILP** for day-ahead global optimization under deterministic assumptions,
- **MILP + PSO**, where particle swarm optimization is used offline to tune multi-objective weights.

Table 2 illustrates the performance under nominal conditions. All methods achieve 100% service satisfaction with zero energy deficit, showing that the charging demand is feasible when arrivals and departures are predictable.

Table 2. *Nominal Scenario Performance.*

Method	Satisfaction rate	Total Deficit (kWh)	Energy Cost
FCFS	1.00	0.0	Baseline
MILP	1.00	0.0	↓
MILP + PSO	1.00	0.0	↓↓

However, a clear difference is observed in operational efficiency. FCFS allocates power based only on current arrivals, without using future information or time-varying prices. By contrast, the MILP plan uses full knowledge of arrivals and departures to move charging away from high-price periods and coordinate power system-wide, leading to a lower energy cost. The integration of PSO further improves this process by tuning the multi-objective trade-offs, resulting in a better and more stable operating point. Although service satisfaction remains unchanged, MILP+PSO improves cost efficiency and reduces sensitivity to parameter selection, as shown by the lowest energy cost in Table 2. These results confirm that deterministic optimization is sufficient and effective when demand is predictable and system stress is low. In this setting, learning-based adaptation brings little additional benefits, which motivates the robustness analysis under uncertainty in the next scenario.

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C. Scenario 2: Robustness Under Uncertainty (Surprise Arrivals)

To evaluate robustness, real-time uncertainty is introduced in the form of surprise vehicle arrivals, that challenge the assumptions of deterministic planning. Additional charging sessions are injected during peak hours to represent unexpected user behavior. Four uncertainty levels are considered, corresponding to 10%, 20%, 30%, and 50% extra arrivals compared with the nominal day. In this scenario, the focus is placed on methods that can operate online:

- **FCFS**, representing non-adaptive scheduling,
- **DRL (Soft Actor-Critic(SAC)-based controller)**, representing the real-time adaptive layer of the framework.

Table 3 reports system performance under increasing levels of surprise arrivals. The reported metrics include service satisfaction rate and total energy deficit, which measure how well the system meets user energy requests before departure.

Table 3. *Robustness Under Surprise Arrivals.*

Surprise arrivals	FCFS Satisfaction	DRL Satisfaction	FCFS Deficit (kWh)	DRL deficit (kWh)
10%	0.948	0.948	1.589	1.589
20%	0.905	**0.952**	7.155	**1.589**
30%	0.882	**0.956**	19.108	**1.589**
50%	0.835	**0.937**	45.680	**2.366**

At low uncertainty (10%), FCFS already performs close to the best, and the DRL controller matches it, indicating that learning-based adaptation is not needed when disturbances are limited. As uncertainty increases, FCFS performance drops quickly. Unmet energy demand increases a lot, and the satisfaction rate goes down. For example, with 30% surprise arrivals, the total energy deficit exceeds 19 kWh, and it increases to 45.68 kWh under extreme stress (50%). By contrast, the DRL approach perform well even if the uncertainty increases (20–50%). By comparing with FCFS method, it reduces the total energy deficit by up to 95%, and keeps a high satisfaction level by respecting the site power limits. This improvement can lead to higher energy cost under extreme stress, showing a clear trade-off between service quality and energy cost. Fig. 2 and Fig. 3 illustrate the results in Table 3. Fig. 2 shows how the total energy deficit changes as surprise arrivals increase. FCFS indicates a sharp increase in energy deficit, which indicates strong sensitivity to demand shocks. On the other hand, the DRL-based controller keeps the deficit nearly constant, even under large perturbations (30–50%). This indicates that learning-based real-time control can handle unexpected demand while still respecting grid constraints.

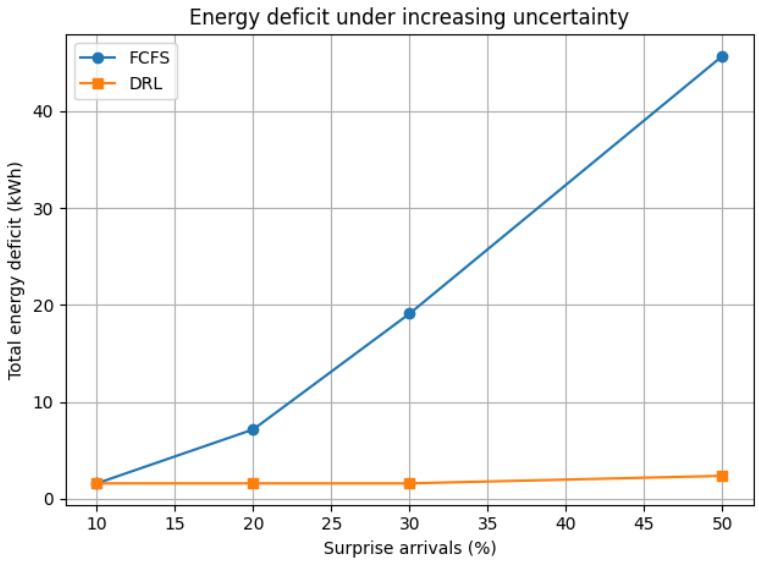


Fig. 2. *Total unmet energy under surprise-arrival demand shocks.*

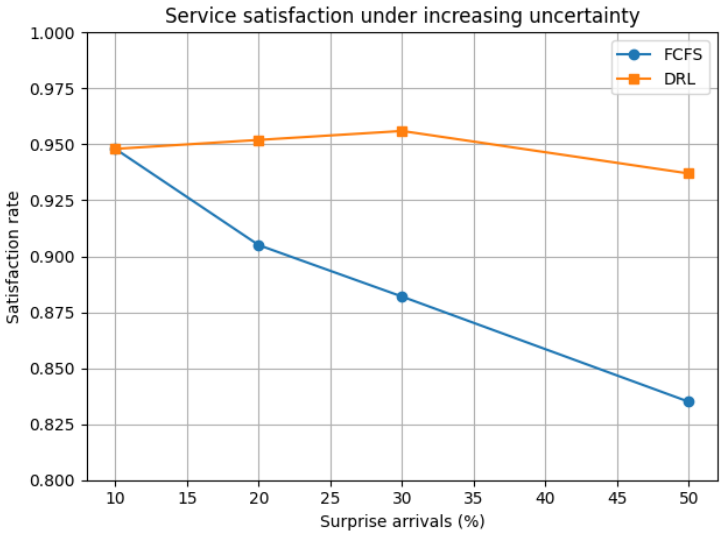


Fig. 3. *Satisfaction rate under surprise arrivals.*

In parallel, Fig. 3 shows the evolution of the service satisfaction rate as uncertainty grows. FCFS indicates a consistent drop in service quality, whereas the DRL controller maintains a high satisfaction level, confirming its robustness in real-time disturbances

D. Discussion: Complementarity and Robustness of the Hybrid Framework

The experimental results confirm that no single optimization approach performs well in different operating environments for EV charging systems. In the nominal cases with a clear demand (Scenario 1), deterministic optimization with MILP uses full information to reduce energy cost and coordinate charging decisions. In this configuration, learning-based adaptation is not necessary, since a simple heuristic can already achieve full-service satisfaction. Then, to improve the framework by making the multi-objective balance more stable, the PSO method is included. It can reduce as well as the sensitivity to parameter settings and makes the operation more consistent,

without adding much extra computation. However, when real-time uncertainty disturbs the planning assumptions (Scenario 2), the previous methods used such as deterministic and non-adaptive heuristics don't perform well. In this case, an online adaptation method like DRL must be used, to adjust power in real time and handle unexpected demand, keep high service quality, and meet the network constraints.

These findings support the suggested framework's SWOT-guided design concept :

- Deterministic planning exploits structural strengths under predictable conditions,
- Metaheuristic tuning mitigates parameter sensitivity and operational variability,
- Learning-based control addresses operational threats arising from uncertainty.

In summary, the results demonstrate that robust EV charging optimization requires a coordinated combination of planning, tuning, and real-time adaptation, rather than relying on a single algorithmic approach.

Conclusion & Future Work

This paper presents a SWOT-guided for a hybrid decision framework for EV charging time optimization. This framework focuses on three main layers: deterministic day-ahead planning with MILP under predictable conditions, offline metaheuristic tuning (PSO) to make the multi-objective problems more stable, and the last layer is a DRL-based real-time control to handle the uncertain parameters. To confirm the performance of this framework, public data from CAN-Data is used to get real charging sessions and test them on a constrained infrastructure (50 kW power limit) including as well as the time-varying electricity prices. The results obtained show clearly that deterministic optimization is robust in nominal conditions, whereas non-adaptive methods degrade quickly in the presence of uncertainty. By contrast, In surprise-arrival scenarios, the DRL layer is more robust: it keeps a high satisfaction rate and reduces unmet energy demand by up to about 95% under strong stress, but energy cost can be higher in extreme cases. This shows a clear trade-off between service quality and energy cost. Overall, These results confirm that MILP, PSO, and DRL perform best when combined, which support the use of hybrid designs for robust EV charging systems. Future work will extend the framework to cover all operational factors (e.g., multi-site networks, microgrids, V2G) and include more detailed battery models and user-preference models.

References

[1] Wang, Y., Wang, H., Razzaghi, R., et al.: Multi-objective coordinated EV charging strategy in distribution networks using an improved augmented epsilon-constrained method. Applied Energy 369, 123547 (2024). https://doi.org/10.1016/j.apenergy.2024.123547

[2] Ren, L., Yuan, M., Jiao, X.: Electric vehicle charging and discharging scheduling strategy based on dynamic electricity price. Engineering Applications of Artificial Intelligence 123, 106320 (2023). https://doi.org/10.1016/j.engappai.2023.106320

[3] Farhadi, F., Wang, S., Palacin, R., Blythe, P.: Data-driven multi-objective optimization for electric vehicle charging infrastructure. iScience 26, 107737 (2023). https://doi.org/10.1016/j.isci.2023.107737

[4] Cao, G., Chang, L.: Optimal Charging Strategy of Dynamic Electricity Price for Electric Vehicles Based on Improved Particle Swarm Optimization. Journal of Electrical Engineering & Technology 20, 1245-1254 (2025). https://doi.org/10.1007/s42835-024-02057-6

[5] Yang, Y., Zhang, C., He, J., et al.: Scalable reinforcement learning for large-scale coordination of electric vehicles using graph neural networks. Communications Engineering 4, 457 (2025). https://doi.org/10.1038/s44172-025-00457-8

[6] Helms, M.M., Nixon, J.: Exploring SWOT analysis - where are we now? Journal of Strategy and Management 3(3), 215-251 (2010). https://doi.org/10.1108/17554251011064837
[7] Das, R., Wang, Y., Busawon, K., et al.: Real-time multi-objective optimisation for electric vehicle charging management. Journal of Cleaner Production 292, 126066 (2021). https://doi.org/10.1016/j.jclepro.2021.126066
[8] Singh, P.P., Das, S., Wen, F., et al.: Multi-objective planning of electric vehicles charging in distribution system considering priority-based vehicle-to-grid scheduling. Swarm and Evolutionary Computation 78, 101234 (2023). https://doi.org/10.1016/j.swevo.2023.101234
[9] Zhang, L., Sun, C., Cai, G., Koh, L.H.: Charging and discharging optimization strategy for electric vehicles considering elasticity demand response. eTransportation 18, 100262 (2023). https://doi.org/10.1016/j.etran.2023.100262
[10] Kaur, A.P., Singh, M.: Time-of-Use Tariff Rates Estimation for Optimal Demand-Side Management Using Electric Vehicles. Energy 273, 127243 (2023). https://doi.org/10.1016/j.energy.2023.127243
[11] Fang, B., Li, B., Li, X., et al.: Multi-Objective Comprehensive Charging/Discharging Scheduling Strategy for Electric Vehicles Based on the Improved Particle Swarm Optimization Algorithm. Frontiers in Energy Research 9, 811964 (2021). https://doi.org/10.3389/fenrg.2021.811964
[12] Huo, M., Pang, S., Zhao, H.: Improved PICEA-g-based multi-objective optimization scheduling method for distribution network with large-scale electric vehicles. Scientific Reports 14, 80184 (2024). https://doi.org/10.1038/s41598-024-80184-w
[13] Pang, S., Fan, K., Huo, M.: Charge and discharge scheduling method for large-scale electric vehicles in V2G mode via MLGCSO. Scientific Reports 15, 00265 (2025). https://doi.org/10.1038/s41598-025-00265-2
[14] Chen, Y., Zhao, H., Pang, S., Huo, M.: Optimal scheduling of solar powered EV charging stations in a radial distribution system using opposition-based competitive swarm optimization. Scientific Reports 15, 88758 (2025). https://doi.org/10.1038/s41598-025-88758-y
[15] Boubaker, S., Kraiem, H., Ghazouani, N., et al.: Multi-objective optimization framework for electric vehicle charging and discharging scheduling in distribution networks using the Red Deer algorithm. Scientific Reports 15, 97473 (2025). https://doi.org/10.1038/s41598-025-97473-7
[16] Li, S., Hu, W., Cao, D., et al.: Electric vehicle charging management based on deep reinforcement learning. Journal of Modern Power Systems and Clean Energy 10(3), 719-730 (2022). https://doi.org/10.35833/MPCE.2020.000460
[17] Liu, H., Peng, B., He, X., et al.: Deep reinforcement learning for charging scheduling of electric vehicles considering distribution network voltage stability. Sensors 23(3), 1618 (2023). https://doi.org/10.3390/s23031618
[18] Tushar, W., Yuen, C., Mohsenian-Rad, H., et al.: Reinforcement learning based EV charging management systems: a review. IEEE Access 9, 72478-72498 (2021). https://doi.org/10.1109/ACCESS.2021.3064354
[19] Xiang, L., Zhang, Y., Xu, Z., et al.: Advancements in EV charging optimization: a survey of reinforcement learning approaches. In: Proceedings of ICEMD 2024, pp. 87-94 (2024).
[20] Lu, X., Wang, Y., Zhao, H., Song, W.: A deep reinforcement learning-based charging scheduling approach with augmented Lagrangian for electric vehicles. Applied Energy 376, 124706 (2024). https://doi.org/10.2139/ssrn.4869056
[21] Sun, W., Chen, Y., Zhang, G., et al.: Electric vehicles charging management using deep reinforcement learning considering vehicle-to-grid operation and battery degradation. Energy Reports 9, 10031-10043 (2023).