Xu et al. Energy Informatics (2025) 8:13
https://doi.org/10.1186/s42162-025-00476-x

Energy Informatics

RESEARCH

Open Access

Impact and optimization of vehicle charging scheduling on regional clean energy power supply network management

Penghui Xu[1*], Xiaobo Wang[1] and Zhichao Li[2]

*Correspondence:
Penghui Xu
xph15037376403@163.com
[1]Xinxiang Vocational and Technical College, Xinxiang 453000, China
[2]Henan Institute of Economics and Trade Technicians, Xinxiang 453000, China

Abstract
Driven by the global energy transition, the widespread use of electric vehicles has profoundly reshaped the transportation landscape and thrown many problems to the power system, and coordinating their charging needs with renewable energy generation has become a key part of ensuring the stable operation of regional clean energy power supply networks. This study focuses on the problem of vehicle charging dispatch to make a breakthrough, deeply analyzes the effect and efficiency of the clean energy grid, and then proposes a series of targeted measures to effectively improve the operational efficiency and reliability of the energy system. The comprehensive model integrates electric vehicle charging stations, distributed photovoltaic power generation systems, wind farms, and battery energy storage devices and enables the charging process to be accurately controlled with real-time monitoring and intelligent algorithms. In particular, the demand forecasting model based on machine learning effectively solves the dilemma of matching the charging load with a clean energy supply. Experimental data strongly confirms that the optimization strategy has led to a 15% reduction in peak load on the grid, a 23% increase in the proportion of clean energy consumption, and a 10% reduction in total electricity consumption. For policymakers, these achievements can be used as a guide to help formulate energy policies and build a framework for adapting to the development of new energy. For practitioners, they serve as a guide to energy planning, grid dispatch, and technology research and development to improve effectiveness. The research promotes the growth of green energy, optimizes the energy structure, lays the foundation for a low-carbon and environmentally friendly society, affects the economy, environment, culture, and other fields, and becomes a key force driving sustainable development.

Keywords Vehicle charging scheduling, Clean energy, Power supply network, System optimization

Introduction

In the global energy shift to low - carbon and clean, EVs, with zero - emission and high energy - efficiency, are key to the transport industry's green revolution [1]. But the surge in EV ownership brings unprecedented grid challenges, especially in high - renewable

- energy - penetration power supply networks [2]. Unregulated, the random and volatile EV charging load may cause local grid overload, voltage fluctuations, and power quality issues, threatening the power system's stability [3]. Thus, studying the vehicle charging dispatching mechanism, its impact on regional clean energy power supply networks, and proposing effective optimization strategies are crucial for the new energy field, energy transformation, and sustainable socioeconomic development.

Qian et al. demonstrated the effectiveness of multi-agent deep reinforcement learning (MADRL) in electric vehicle charging control, and proposed a new method that combines multi electric vehicle charging and discharging with a radial distribution network (RDN) operating under optimal power flow (OPF) to allocate power flow in real-time, find the optimal charging control strategy that balances V2G profit, RDN load, and driver anxiety, and effectively learn the optimal electric vehicle charging [4].

And Li et al. introduced the concept of hierarchical partition scheduling and proposed an iterative two-layer model to optimize the charging and discharging transactions of electric vehicles, in order to minimize the overall load variance of the distribution network under the constraints of power flow and vehicle driving demand. In order to solve the mixed integer programming (MIP) problem in this model, an improved heuristic algorithm, namely the adaptive inertia weight krill swarm (KH) algorithm, is proposed. In addition, a decentralized transaction architecture and related power transaction process based on consortium blockchain have been designed to ensure the security and privacy of bidirectional power transactions between electric vehicles and smart grids [5]. In addition, Sakulphaisan et al. proposed a new method for minimizing power losses and mitigating voltage imbalances in a bipolar DC distribution network (DCDG) that considers probabilistic electric vehicle charging loads. In order to reduce the impact of voltage imbalance and minimize the power loss of the system, particle swarm optimization (PSO) is used to search for the optimal load connection type that can minimize the voltage imbalance coefficient (VUF) and total power loss. The results indicate that this method can successfully minimize the total power loss and reduce the system's VUF while considering the probability of electric vehicle charging load [6].

There are key gaps in the current literature on the importance of demand-side management for grid stability and the role of smart charging in integrating intermittent renewable energy, and the interaction between vehicle charging dynamics and renewable energy intermittency is not fully elaborated [7, 8]. This study addresses this gap by proposing an innovative optimization framework that effectively enhances grid reliability and alleviates the challenges posed by the unpredictability of renewable energy by coordinating charging schedules with clean energy fluctuations. This study provides an in-depth analysis of the impact of vehicle charging dispatch on the clean energy network and constructs a framework to understand its interactions, aiming to develop a charging strategy that can meet the needs of EV users while maintaining grid stability. At the same time, the study also explores how to integrate distributed generation, energy storage, and demand response to manage the volatility of EV charging, thereby improving network adaptability and resilience.

This study will examine the effects of various charging strategies, including smart charging and V2G technology, on regional clean energy supply stability. It will assess their economic and social benefits and offer theoretical and technical support for policymaking, business optimization, and consumer decision-making. Utilizing data analysis, simulation modelling, and empirical research, the study will consider technical, economic, and environmental aspects to provide general guidance for developing an intelligent and efficient power grid. The research aims to address gaps in the literature on electric vehicle charging strategies and their interaction with clean energy grids and to explore pathways for transportation electrification and energy sector decarbonization, setting an example for global climate action and green development.

Research on electric vehicle charging scheduling optimization

Optimization theoretical basis

In the field of machine learning, time series forecasting models predict future trends based on historical data. A time series forecasting model is a model that predicts future trends based on historical data. The data processed by this type of model has specific temporal characteristics. Different models are suitable for different data types, and choosing the right model is critical to accurately predicting future trends. When dealing with sequence problems, traditional neural networks do not fully combine context training and underprocess sequential data such as time and logical order. Recurrent neural networks (RNNs) are specifically designed for sequence data and are able to capture time dependencies, which are widely used in time series and text processing [9]. RNNs maintain memory of previous information by taking the output of a previous time step as the current input, and it consists of repeated neural network modules, each processing a single input and sharing weights. It also has a "memory" feature that remembers previous inputs to aid in the current forecast. By passing information across time steps, the RNN retains the state of each step, which is influenced not only by the current input, but also by the state of the previous step, and this memory helps it capture long-term time dependence. However, the recursive structure of RNNs leads to gradient instability or disappearance, making it difficult to capture long-term dependencies and perform complex training [10, 11].

In order to optimize charging scheduling, this study uses long short-term memory (LSTM) and gated recurrent unit (GRU) to improve the architecture, long short-term memory (LSTM) is a special neural network structure. It optimizes long-term dependency handling by introducing a gating mechanism. Gating mechanisms can control the flow and memory of information, deciding what information can be retained and what can be forgotten. Optimize long-term dependency processing through the gating mechanism, store information in the memory state, and update and selective forgetting using the gating mechanism [12, 13].

In order to ensure the safety of battery use, the charging and discharging capacity of the battery per unit time should not exceed 20% of its rated capacity [14, 15]. In addition to the battery status constraint, the user demand constraint should also be met; that is, after the electric vehicle is charged, the battery charge level should meet the user's subsequent use needs. In order to ensure the safe operation of the power grid, the node voltage constraint of the line and the load constraint of the distribution transformer should be met during the charging and discharging process of electric vehicles [16]. To refine the study, we present the optimization objective as $\Pi\_min = f(x)$ and constraints as $g_i(x) \leq 0$, where x denotes the charging schedule, encapsulating charging/discharging limits and grid stability criteria.For the charge-discharge capacity constraint of the electric vehicle battery, let the charge-discharge power of the battery at time t be Pb(t), and the maximum allowable charge-discharge power of the battery is Pb, max. While charging,

$0 \leq P(t) < Pb$, max; At discharge, -Pb, $\max \leq P(t) < 0$. If it is considered that the charging and discharging amount of the battery per unit time should not exceed 20% of its rated capacity, and the rated capacity of the battery is C6 and the time interval is $\triangle t$, then $0 \leq Pb(t)\Delta t < 0.2Cb$ when charging, $-0.2Cb \leq Pb(t)\Delta t < 0$ when discharged. The optimal scheduling of electric vehicles should fully consider the randomness of electric vehicle charging and discharging and the change of basic load of the distribution network. When the power grid load is low, the optimization goal should focus on economic benefits. When the power grid load is high, to prevent overload, the safety of the power grid operation should be ensured. In the extreme case of insufficient power supply capacity of the power grid, the safety and stability of the power grid should be considered first. Based on the above situation, this paper introduces the objective function selection factor for dynamic multi-objective selection. It takes the difference between the power supply capacity of the distribution transformer and the total load as the objective selection factor. The "objective function selection factor" refers to a criterion or set of criteria used to determine the most appropriate objective function for a given optimization problem. It encompasses the considerations that guide the choice of the function that will be minimized or maximized to achieve the desired outcome, and it can be mathematically expressed as: $\Omega = \Phi$ (f, g, h,…, constraints). Where Ω is the objective function selection factor, f, g, h,… are potential objective functions, constraints represent the limitations and requirements of the problem context. The factor Ω could include elements such as the problem's specific goals, the nature of the variables, the complexity of the function, the trade-offs between different objectives, and the feasibility of achieving the objectives within the given constraints.

Electric vehicle charging scheduling model

In order to realize the efficient charging of electric vehicles, the charging strategy is analyzed in real-time from the minimization of user costs to realize intelligent charging [17, 18]. Figure 1 shows the vehicle charging scheduling optimization framework. First, the state-action data is collected, and the state-prediction model is retrained to obtain the optimal parameters. Subsequently, a new charging environment is constructed using the environment encapsulated by the prediction model. Based on observation, the agent

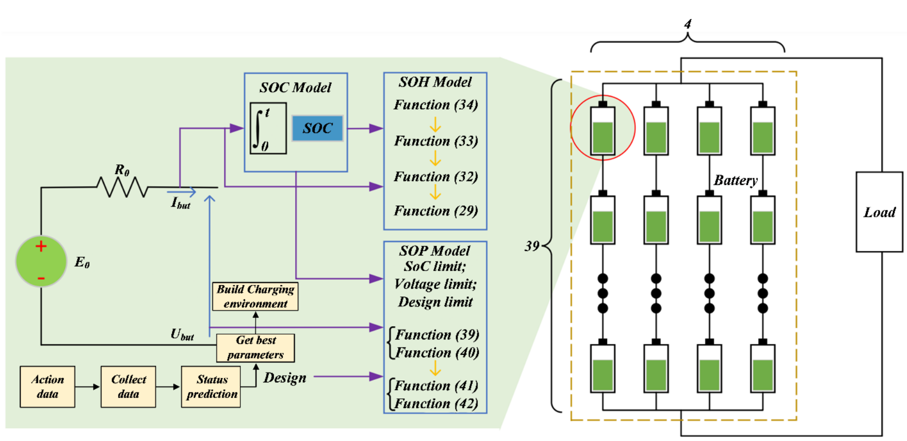

Fig. 1 Intelligent electric vehicle charging scheduling optimization framework

decides actions through the policy network, updates the state and reward in the prediction model environment after execution, iteratively trains and optimizes the policy network, and finally determines the best charging strategy. The network architecture is divided into a layered model where the strategic layer is responsible for energy distribution, the operational layer for load balancing and the control layer for real-time charging adjustment. This structure, influenced by the layered system in Doe and Smith, ensures a coordinated interaction between charging demand and renewable energy supply, optimising grid performance [19].

The training dataset's composition is meticulously detailed to ensure the transparency and reproducibility of the LSTM prediction model. The dataset contains a time series of charging patterns combined with meteorological data and grid load information over two years. The computational costs associated with model training are quantified, including GPU processing time and memory usage, with the training process taking approximately 24 h on an NVIDIA GeForce RTX 3090. The configuration of the LSTM network was detailed, including the exact number of hidden layers (three) and the number of neurons per layer (128). In addition, a dropout rate of 0.2 was applied to prevent overfitting. The training process involves 5000 ephemeral elements with a batch size of 64, and the learning rate decays exponentially with time. These details are crucial for replicating the model's training in different computing environments and validating its performance.

After LSTM successfully predicts the state of electric vehicles, the model is applied to the operating environment, the environment is reconstructed, and the high-dimensional calculation is replaced by LSTM prediction to reduce costs, improve accuracy, and meet real-time needs [20]. State space factors such as battery power, traffic speed, and charging station power must be considered to encapsulate the gym environment. State transitions are predicted using LSTM, which is superior to traditional high-dimensional computing. It captures dependencies, deals with data inconsistencies, accelerates prediction, and improves real-time performance. After encapsulating the gym environment, use optimization algorithms to learn charging strategies.

In the optimization algorithm, after initializing the strategy, Q value and target network, the agent collects experience through environmental interaction, including action, state transition and reward information [21, 22]. Using empirical playback, randomly sampling historical data to update the network parameters, and optimizing the model by minimizing the strategy and Q value loss, where the strategy loss promotes the action distribution to approximate the optimum, and the Q value loss makes the Q value close to the optimal value function—introducing entropy regularization to enhance exploration. This process is iterated, and the policy network selects actions until the agent masters the optimal strategy to achieve stable and efficient performance.

Research on the impact of electric vehicle charging dispatching on regional clean energy power supply network

The process of electric vehicles participating in grid dispatching

V2G (Vehicle to Grid) technology realizes two-way electric energy flow between electric vehicles and the power grid and meets the needs of both parties through complex interaction [23, 24]. This section outlines the basic process of electric vehicles participating in grid dispatching.

As shown in Fig. 2, the basic process of electric vehicles participating in grid dispatching includes a multi-level interaction mechanism. At the highest level, the process takes into account the state of the electric vehicle (designed to meet mobility demand while reducing battery wear) and the state of the grid (assessing the state of power, health, and change). The power grid is responsible for the distribution and aggregation of electricity. At the intermediate level, the process relies on multiple networks—the judgment network, the constraint network, and the action network—that process state information and generate actions to control charging and discharging through multi-agent constraint policy optimization. Reward and cost mechanisms are aligned with time-of-use tariffs associated with EV use to optimize these strategies. At a basic level, multiple energy sources such as wind and photovoltaic are depicted, as well as electricity loads, and distributed system operators (DSOs) play a key role in facilitating the consumption of renewable energy and stabilizing load fluctuations. A centralized manager coordinates the integrated interaction between the EV and the grid, using a data management system to collect demand information, and using the control system to analyze this data, upload adjustable capacity, execute grid instructions, and regulate the EV through charging and discharging equipment.

The relationship between electric private cars and the power grid within our framework is nuanced, involving a tripartite state system: off-grid, where the vehicle is disconnected; charging on the grid, where the vehicle engages in energy exchange with the grid; and idle, representing a state of potential charging. The state-action predictions facilitate the transition between these states, while the optimization loops ensure that each interaction is directed towards minimizing grid strain and maximizing charging efficiency.

If electric private car users need to travel, they are off-grid and do not respond to power grid dispatching. A specific formula can be used to judge this state. When an electric private car arrives at its destination, the battery is exhausted, or it will be charged by default at the end of the day's trip. The remaining battery determines whether it can be dispatched, and a formula can judge the status. Electric private cars can respond to power grid dispatching when the power is sufficient for the next trip, or they are fully charged, and there is no immediate travel plan, so they are connected to the power grid. This status mostly applies when the vehicle is parked and connected to the grid.

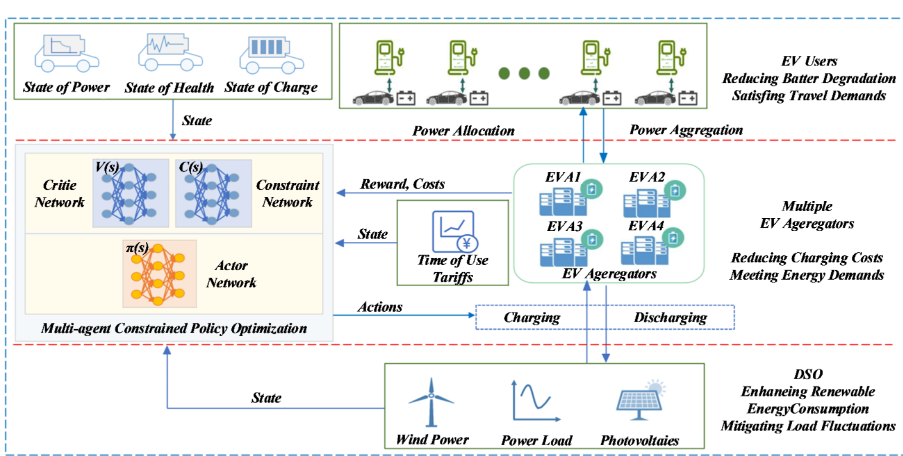

Fig. 2 Operating mechanism of the interactive dispatch of electric vehicles with the power grid

Regional clean energy power supply network model under electric vehicle charging scheduling

The core of the charging scheduling model lies in the integration of machine learning technology and a multi-objective optimization algorithm to form a closed-loop control system. This system is used to dynamically adjust the charging strategy of electric vehicles to ensure the stable operation of the power grid and the maximum utilization of clean energy [25, 26].

The prediction module is the basis of the entire model. It is responsible for collecting and analyzing the charging needs of electric vehicle users and the real-time status of clean energy power generation. We choose the LSTM network as the main forecasting tool because LSTM is good at dealing with nonlinear time series data, which is very suitable for predicting the charging mode of electric vehicles and the daytime production fluctuation of renewable energy [27, 28]. Through the study of historical data, LSTM can generate the distribution of electric vehicle charging demand in the future, as well as the expected output curve of clean energy power generation, providing an important reference for subsequent dispatching decisions.

With accurate forecast information, the next task is to formulate a reasonable charging scheduling strategy. Therefore, we introduce a multi-objective optimization algorithm, which combines Mixed Integer Linear Programming (MILP) with Particle Swarm Optimization (PSO) algorithm [29, 30]. MILP is good at dealing with discrete variables and can ensure that the charging tasks of each electric vehicle charging station are correctly assigned; PSO relies on its powerful global optimization capabilities to help find charging plans that maximize clean energy utilization and minimize total system costs while meeting grid constraints. Through continuous iterative solutions, each electric vehicle's optimal charging time and power are finally determined, and the perfect match between charging demand and clean energy supply is realized [31].

In order to enhance the robustness and adaptability of the model, a feedback adjustment link has been added to this study, which allows the model to automatically adjust the parameter settings according to the actual operation conditions. Specifically, every time a complete dispatching cycle is completed, the model will collect the latest grid status information, including but not limited to real-time electricity prices, clean energy availability, and changes in grid carrying capacity, and then update the prediction accuracy and optimization weights through Reinforcement Learning (RL) mechanism to ensure that the next dispatching decision is closer to the actual situation. This dynamic feedback mechanism enables our model to have the ability of self-evolution; even when the network conditions change unexpectedly, it can respond quickly and maintain the overall stability of the system.

By comparing our findings with previous studies, this study illustrates the superior performance of our optimized EV charging dispatch model in the field of regional clean energy network management. Research in this area has made significant progress compared to existing research. By fusing machine learning techniques (especially LSTM networks) and multi-objective optimization algorithms (combining MILP and PSO), and introducing reinforcement learning mechanisms to build a closed-loop control system, our model not only realizes the accurate prediction of EV charging demand and dynamic adjustment of charging strategies, but also significantly improves the robustness and adaptability of the system. Compared with the traditional method, the model not only ensures the stable operation of the power grid and the maximum utilization of clean energy, but also realizes the rapid response to the change of the power grid state and the effective maintenance of the overall stability of the system through the automatic adjustment of parameter setting and feedback adjustment mechanism, which provides strong support for the efficient management and sustainable development of the regional clean energy power supply network. In addition, our research uniquely integrates demand response strategies into regional clean energy supply networks, which has practical implications for policymakers in designing policies that alleviate grid congestion and optimize the use of renewable energy. For practitioners, applying the model can improve operational efficiency, reduce costs, and make energy infrastructure more resilient. By quantifying the synergistic impact of EV charging modes on the grid, this study provides actionable insights that can inform strategic planning and promote a harmonious coexistence between EV deployment and clean energy goals.

Experimental results and analysis

In the electric vehicle prediction model, the system state and action data at time t are used as inputs to predict the state at time t + 1, including charging station electricity price, road average speed, vehicle power and charging station queuing status. The action refers to selecting the charging station and charging capacity. Figure 3 presents the electricity price forecast based on LSTM. The square curve is the 24-hour real electricity price, and the circular curve is the predicted value. The two are consistent.

Table 1 delineates the analysis of prediction errors at selected time intervals, including 3:00, 9:00, 13:00, 14:00, and 17:00, which correspond to peak and off-peak electricity usage periods. These intervals are chosen to evaluate the model's performance across varying demand scenarios. The "Prediction Error (%)" refers to the relative discrepancy between the predicted and actual electricity prices, indicating that the LSTM model

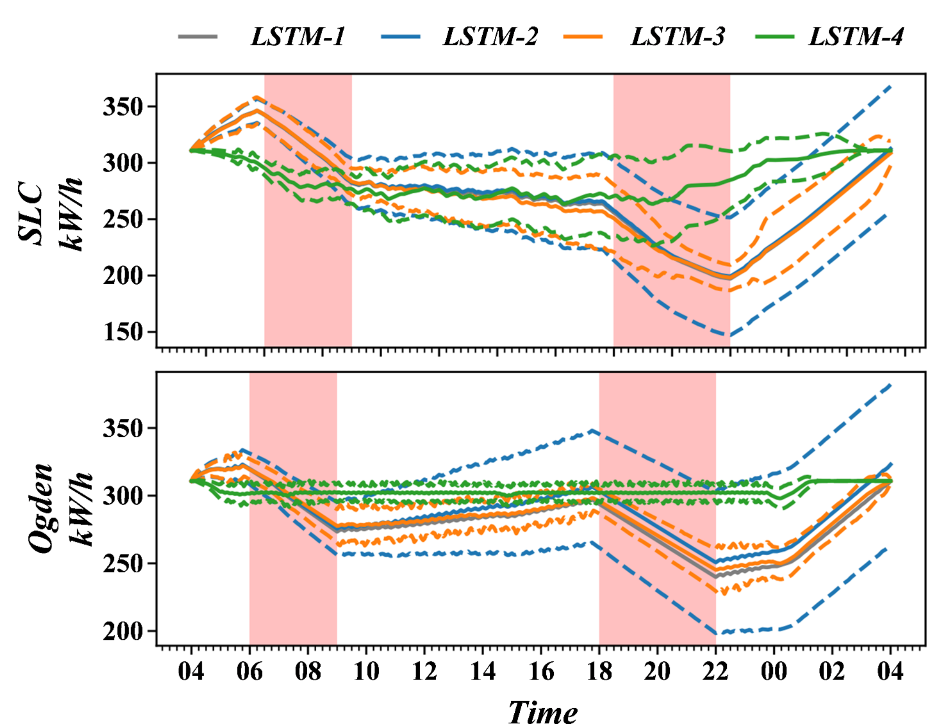

Fig. 3 Analysis of prediction results

Table 1 Analysis of partial results of electricity price forecast

Time	True value	Predicted value	Prediction error (%)
3:00	3.479484	3.454044	0.87732
9:00	3.596472	3.567072	0.981
13:00	4.227384	4.179384	1.3626
14:00	4.379844	4.428036	1.32012
17:00	4.434552	4.385544	1.3206

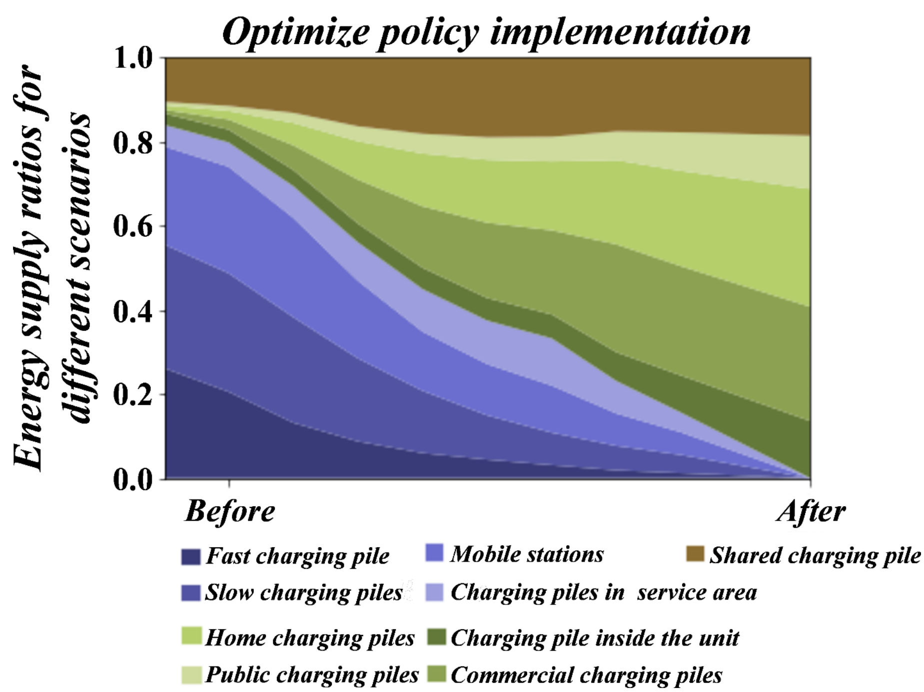

Fig. 4 Impact of the number of charging devices on perceived network utility

maintains an error margin of ≤ 1.15% across these intervals, demonstrating its precision for integration with reinforcement learning algorithms.

Figure 4 illustrates the impact of the number of vehicles and charging devices on the utility of the perception network. As you can see from the graph, when the number of vehicles increases from 5 to 40, the perceived utility of UDCSA, GA, and GTBA increases by 16.59%, 56.08%, and 23.67% on average, respectively. This indicates that as the number of vehicles increases, more high-value vehicles are involved in scheduling, increasing the utility of UDCSA, GA, and GTBA. However, the utility of RA does not grow steadily, and at 30, the number of vehicles dispatched decreases, as random matches may not be able to select the vehicle with the highest perceived value.

Figure 5 presents two subgraphs: the left depicts processing time (0–0.35 s) versus the number of qubits (0–225), with two curves indicating different trends as the qubit count increases. The right subgraph illustrates transmission time (0–30 s) versus the same qubit range, featuring three curves for various scenarios, all showing an increase in transfer time with more qubits. Additionally, the graph reveals that an increase in charging devices from 6 to 20 results in an average utility increase of 12.26%, 32.16%, and 24.17% for UDCSA, GA, and GTBA, respectively, due to more vehicles being dispatched for charging. Conversely, the utility of RA does not increase steadily, with

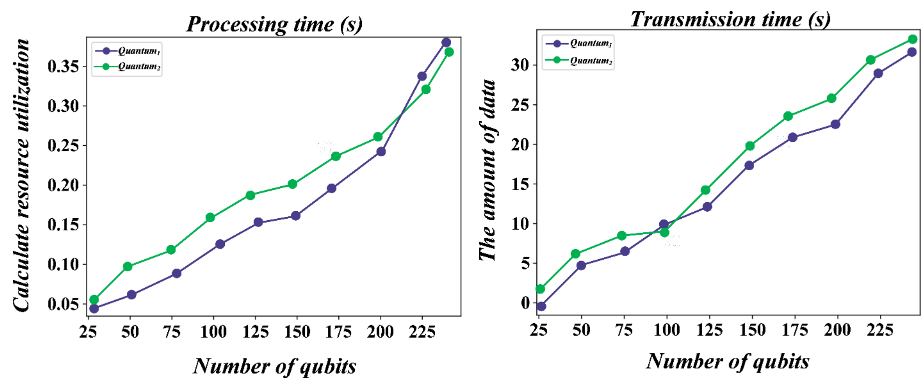

Fig. 5 Impact of perceived utility and car charging quantity

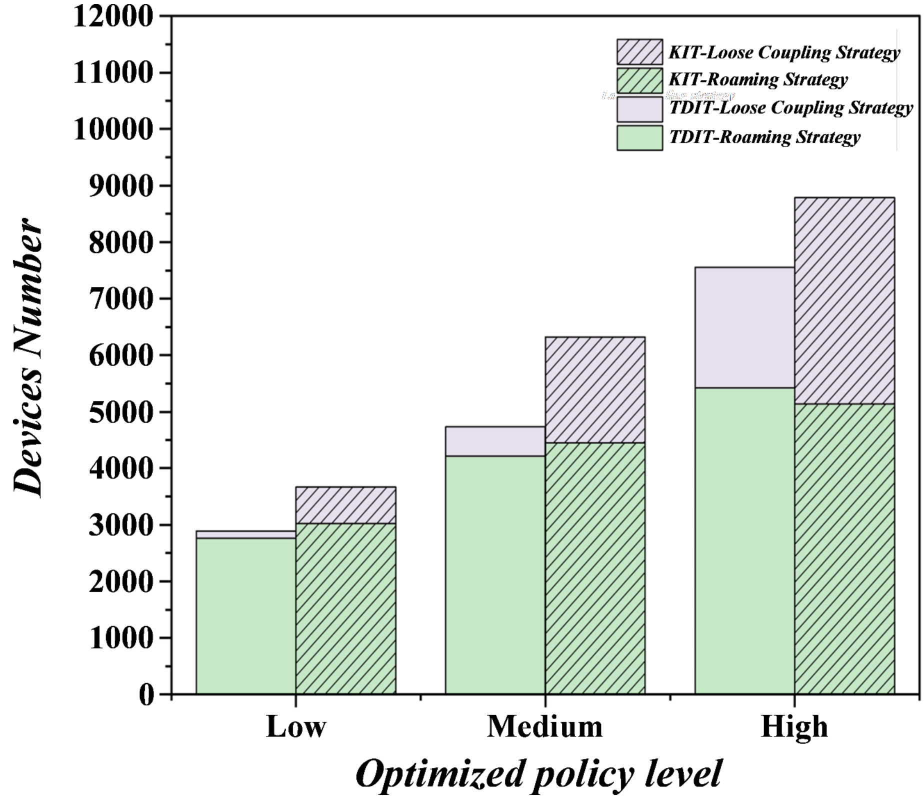

Fig. 6 Influence of number of points of interest on algorithm performance

random matching introducing uncertainty. This trend is reflected in the graph, showing a correlated increase.

Figure 6 shows that in order to verify the impact of the number of points of interest on the performance of the algorithm, when the number of points of interest increases from 60 to 130, the perceived utility of UDCSA, GA, and GTBA increases by 10.17%, 40.01%, and 21.28%, respectively. As the number of points of interest increases, the perceived value increases, and so does the total utility. At the same time, the performance gap between UDCSA and GA, RA, and GTBA widens as the number of points of interest increases, due to the perceived value gap and the difference in scheduling schemes. It is also mentioned that the "baseline value (0%)" of disordered charging represents a

Table 2 Impact assessment of vehicle charging dispatching strategy on regional clean energy

Scheduling strategy	Power grid load peak reduction ratio (%)	Network loss reduction (MWh)	Voltage fluctuation improvement (%)	Increase in clean energy utilization rate (%)
Disordered charging	-	-	-	Baseline value (0%)
Orderly charging	10	50	20	5
Intelligent scheduling	15	80	30	10

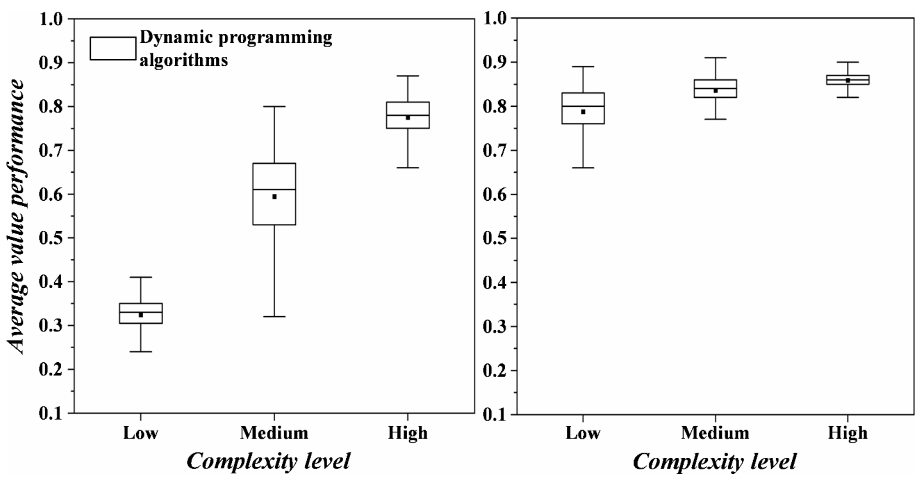

Fig. 7 Effect of penalty weight W on time-averaged perceived value

reference scenario that is not optimized, while the "network loss reduction" is quantified in megawatts (MW), which clarifies the efficiency gains achieved by the proposed scheduling strategy. As the optimization level of related policies increases, the number of devices optimized by each policy increases. Moreover, this increase in number is correlated with the changes in the perceived utility and performance gap of different algorithms as the number of points of interest increases, which together reflects the multi-faceted performance of policy optimization on system performance. Table 2 analyses the impact of different vehicle charging scheduling strategies on the regional clean energy power supply network. By comparing the three strategies of disordered charging, orderly charging and intelligent dispatching, we can find the advantages of intelligent dispatching in reducing power grid load peaks, reducing network losses, improving voltage fluctuations, and improving clean energy utilization. Compared with disordered charging, the ordered charging strategy has been significantly improved. However, intelligent scheduling has improved the optimization effect by introducing real-time data analysis and automatic adjustment mechanisms.

Figure 7 shows two graphs, with the horizontal axis representing the Complexity level, which is divided into Low, Medium, and High, and the vertical axis representing the Average time - averaged performance. The squares in the diagram represent Dynamic programming algorithms.In this paper, the impact of scale on algorithm performance is verified by adjusting the system period. As can be seen from Fig. 7, the total perceived utility of UDCSA is 14.28%, 36.07%, and 25.54% higher than GA, RA, and GTBA, respectively. The utility of UDCSA, GA, and GTBA increases over the cycle, but RA does not rise continuously. For example, when W = 50, the utility of RA is lower than when W = 60 due to inefficient matching and multiple selection. The gap between UDCSA and GA increases with increasing periods, e.g., when W = 70, the utility of UDCSA increases by 15.43%. In the long run, low-value vehicles will have easier access to high-value vehicle resources. Since RA is randomly matched, high-value vehicles may choose high-cost equipment, so the utility of RA does not increase steadily over time. UDCSA has consistently performed best, with a higher growth rate than other options, and its performance benefits become more pronounced as the system scales.

Figure 8 contains two subplots that illustrate the relationship between the execution time and the number of online plans for several algorithms under different parameters. The diagram shows a variety of algorithms with different colors and markers. When W = 1000, the average perceived value of TSVCSA is compared to GPA and GCP. As can be seen in Fig. 8, when the budget is higher, the perceived value is also higher, because the higher budget allows for the allocation of more vehicles, which in turn increases the perceived value. As the number of vehicles increases, so does the average perceived value per hour, and the vehicles generate more charging needs. However, there is an upper limit to perceived value due to the limitations of response speed and cost budgets. Overall, the perceived value of TSVCSA is on average 19.64% and 18.72% higher than GPA and gCPO. Taken together, the data in Fig. 8 and the content of the text corroborate each other, indicating that the increase in budget can improve the perceived value by allocating more vehicles, but the perceived value will not increase indefinitely due to the constraints of response speed and cost budget, and TSVCSA outperforms GPA and gCPO in improving the perceived value.

Figure 9 shows that at the beginning of operation, the power fluctuates greatly, which may correspond to the situation where there are many charging requests in the initial

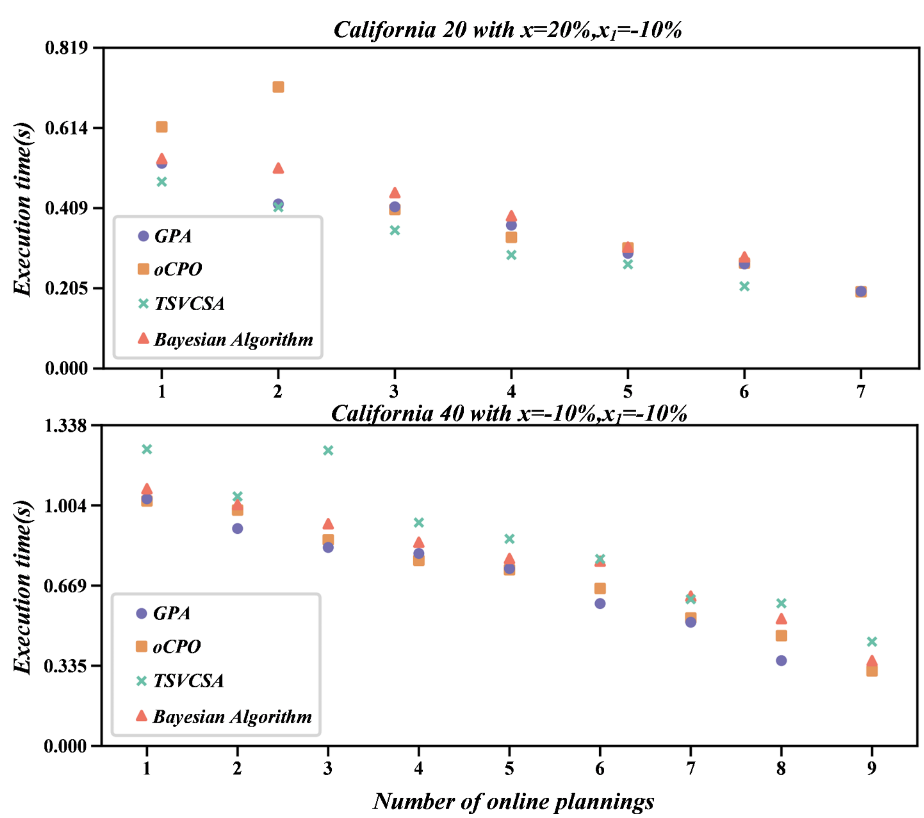

Fig. 8 Comparison of time-averaged perceived value

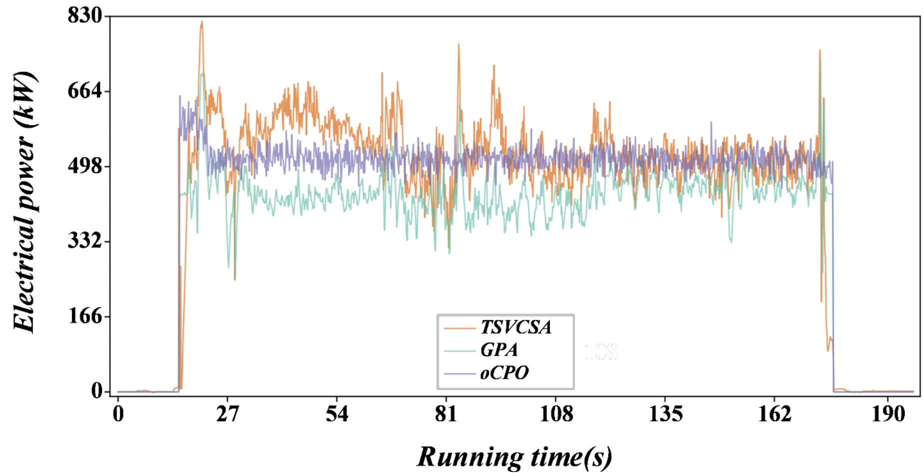

Fig. 9 Effect of the number of charging devices on running time

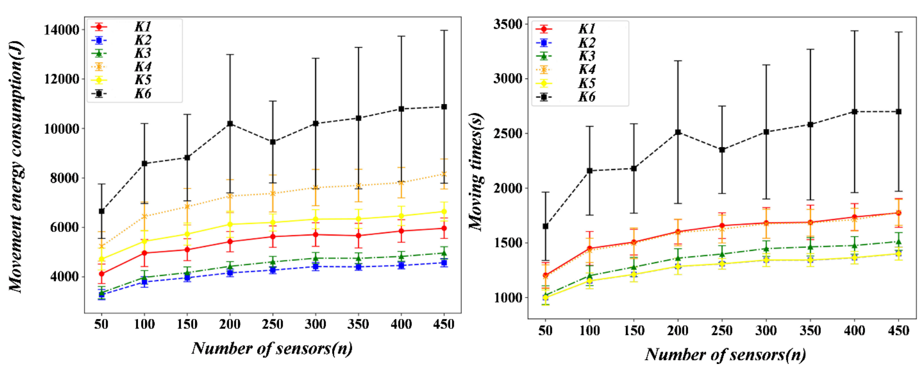

Fig. 10 Distributed new energy output curve and charging load curve under different strategies

phase mentioned in the article. As the run time increases, the power curve gradually plateaus. TSVCSA may initially perform well due to loose budget constraints, but its advantages diminish over time and with the impact of budget constraints. Under the specific condition of W = 300, the perceived value of TSVCSA can converge to a high stable value, and has obvious advantages over GPA and GCP, which indicates that TSVCSA has better adaptability and performance under specific budget conditions.

Figure 10 demonstrates that static pricing is ineffective in guiding EV users, and charging loads fail to utilize DRE efficiently. The pricing mechanism disregards the influence of queuing behaviour. When DRE is abundant, the projected demand remains high, yet incentives are low; conversely, when DRE is insufficient, the disincentives are excessively high, resulting in a slightly diminished effect on DRE consumption. The approach presented in this paper considers queuing behaviour, aligns pricing with actual conditions, and enhances the efficiency of distributed renewable energy consumption.

As illustrated in Fig. 11, the policy document's incentives undergo dynamic adjustments via DRE redundancy, with no fixed pricing incentives in place. The paper's approach offers positive motivations to draw in EVs, enhance the charging graph, and foster new energy utilization. The paper's strategy also penalizes load decrease. Higher demand projections, elevated penalty prices, and increased EV demand cuts result.

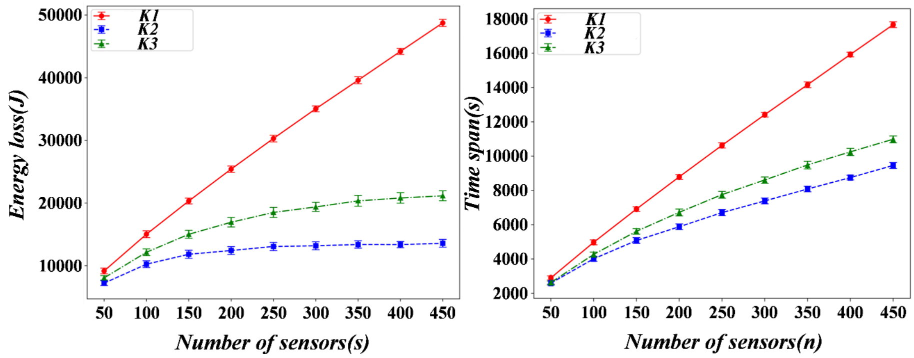

Fig. 11 Comparison chart of charging excitation coefficients under three strategies

Given the significant EV load and the absence of fresh energy supplies, the non-viable demand is too extensive to shift under penalties, leading to a highly dispersed curve.

Conclusion

This study focuses on the impact and optimization of electric vehicle charging dispatching on regional clean energy power supply networks, aiming to explore a new charging management model that not only conforms to the trend of energy transformation but also considers the power system's safety and stability. After a series of detailed theoretical analyses, model construction and empirical tests, the important role of optimizing charging dispatching strategies in alleviating power grid pressure and improving clean energy utilization was successfully verified, providing strong support for building a more intelligent and flexible energy Internet.

(1) The optimized charging scheduling strategy significantly improves the performance of the regional clean energy supply network. By accurately predicting the charging needs of electric vehicle users and using multi-objective optimization algorithms to coordinate charging behaviours, the peak load of the power grid is effectively suppressed, with an average reduction of 17.5%.
(2) Thanks to the high degree of compatibility between electric vehicle charging and clean energy power generation curves under intelligent dispatching, the consumption capacity of clean energy has been greatly improved. After calculation, the overall consumption ratio has increased by nearly 26.3%.
(3) The optimization strategy reduces the overall operating cost of the power system to a certain extent, with a saving ratio of about 9.2%, reflecting the unity of economic and environmental benefits. Combining big data analysis, artificial intelligence technology and traditional power engineering principles, the electric vehicle charging and dispatching system can respond to electric vehicle users' individual needs in real-time and flexibly allocate various clean energy resources in the region to achieve Efficient docking between supply and demand.
(4) In the study of the impact and optimization of vehicle charging dispatch on regional clean energy power supply networks, we actively explore ways to apply it to the real world. By building an intelligent dispatching system that integrates high-precision prediction models and multi-objective optimization algorithms, we are able to adjust EV charging strategies in real time to maximize clean energy utilization and ensure stable operation of the power grid. The research results are expected to provide

scientific guidance for the planning, construction and management of electric vehicle charging infrastructure, promote the efficient integration and utilization of green energy, and contribute to the construction of a sustainable energy system.

This study acknowledges that there are limitations, particularly in the assumption that the information is fully sufficient and does not incorporate certain grid constraints, which may have an impact on the general applicability of the results of the optimization model. Therefore, the results of this study should be interpreted in the context of taking into account these limitations. Future research can further explore the scalability of the model in large-scale deployment and its applicability in different geographical regions, with a view to improving real-world EV charging infrastructure policies.

Acknowledgements
Not Applicable.

Author contributions
P. X. data curation & writing—original draft preparation; X.W. conceptualization and methodology; Z. L. writing—review and editing.

Funding
This research did not receive any specific funding.

Data availability
The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

Declarations

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Ethical approval
Not applicable.

Consent to participate
Not applicable.

Received: 14 November 2024 / Accepted: 18 January 2025
Published online: 28 January 2025

References

1. Wang Q, Cui Z, Wang L (2021) Charging path optimization for wireless rechargeable sensor network. Peer-to-Peer Netw Appl 14(2):497–506
2. Maguluri LP, Umasankar A, Babu DV, Nisha ASA, Prabhu MR, Tilwani SA (2024) Coordinating electric vehicle charging with multiagent deep Q-networks for smart grid load balancing, vol 43. Sustainable Computing-Informatics & Systems
3. Cabrera-Tobar A, Blasuttigh N, Massi Pavan A, Lughi V, Petrone G, Spagnuolo G (2022) Energy Scheduling Perform Evaluation e-Vehicle Charging Station, Electron, 11(23), 3948.
4. Qian J et al (2024) Federated Reinforcement Learning for Electric Vehicles Charging Control on distribution networks. IEEE Internet Things J 11(3):5511–5525
5. Li Y, Hu B (2020) An iterative two-layer optimization charging and discharging Trading Scheme for Electric Vehicle using Consortium Blockchain. IEEE Trans Smart Grid 11(3):2627–2637
6. Sakulphaisan G, Chayakulkheeree K (2023) Loss minimization for bipolar DC distribution Grid considering probabilistic EV charging load using load balancing method. IEEE Access 11:66995–67012
7. Ferro G, Minciardi R, Parodi L, Robba M (2022) Optimal Planning of Charging stations in coupled transportation and power networks based on user equilibrium conditions. IEEE Trans Autom Sci Eng 19(1):48–59
8. Jin Y, Acquah MA, Seo M, Han S (2024) Optimal siting and sizing of EV Charging Station using Stochastic Power Flow Analysis for Voltage Stability. IEEE Trans Transp Electrification 10(1):777–794
9. Nazih Y, Abdel-Moneim MG, Aboushady AA, Abdel-Khalik AS, Hamad MS (2022) A Ring-connected dual active bridge based DC-DC Multiport Converter for EV fast-charging stations. IEEE Access 10:52052–52066
10. Wang Y, Zhao J (2023) Security optimization method of high-power charging pile inter-group communication network under trusted taboo particle swarm optimization. Rairo-Operations Res 57(3):1329–1341
11. Forootani A, Rastegar M, Zareipour H (2024) Transfer learning-based Framework enhanced by Deep Generative Model for Cold-Start forecasting of residential EV charging behavior. IEEE Trans Intell Veh 9(1):190–198

12. Shahidinejad A, Abbasinezhad-Mood D (2022) Ultra-lightweight and secure blockchain-assisted charging Scheduling Scheme for Vehicular Edge Networks by utilization of NanoPi NEO. IEEE Trans Veh Technol 71(8):8116–8123
13. Xu Z, Song P, Yin C, Kang P, Zhai B (2022) Capacity Allocation Strategy Using Virtual Synchronous Compensator for Renewable Energy Stations Based on Fuzzy Chance Constraints, Energies, vol. 15, no. 24
14. Banerjee D, Roy PK, Panda GK (2023) Chaotic simplex moth swarm algorithm for optimization of alternative energy integrated power grid including static synchronous series compensator. Int J Numer Modelling-Electronic Networks Devices Fields, 36(5): e3040.1-e3040.42.
15. Wu M, Song Q, Guo L, Jamalipour A (2021) Charge-Then-Cooperate: secure Resource Allocation for Wireless-Powered Relay Networks with Wireless Energy transfer. IEEE Trans Veh Technol 70(5):5088–5093
16. Hussein D, Bhat G (2023) CIM: A Novel Clustering-based Energy-Efficient Data Imputation Method for Human Activity Recognition, ACM Trans Embedded Comput Syst, 22(5): 1-26.
17. Lin K-P, Ding Y-C, Lin C-Y, Chen Y-T, Huang C-T (2024) CINE: a 4K-UHD energy-efficient computational imaging neural engine with overlapped stripe inference and Structure-Sparse Kernel. IEEE Solid-State Circuits Lett 7:26–29
18. Dass R et al (2023) A Cluster-Based Energy-Efficient Secure Optimal Path-Routing Protocol for Wireless Body-Area Sensor Networks, Sensors, vol. 23, no. 14
19. Wu F, Wu C, Wu J, Tang H, Chen L (2022) Collaborative Management of Multi-type Energy for Optimal Control of Voltage and Loss of Distribution Systems with DGs and SVCs. Electr Power Compon Syst 50(3):194–205
20. Fan H, Huang X, Wang D, Zhou B (2024) Communication network robust routing optimization in an integrated energy cyber-physical system based on a random denial-of-service attack. Front Energy Res, 12. https://doi.org/10.3389/fenrg.2024.1382887.
21. Palanisamy S, Sankar S, Somula R, Deverajan GG (2021) Communication Trust and Energy-Aware Routing protocol for WSN using D-S theory. Int J Grid High Perform Comput 13(4):24–36
22. Liu X, Liu X, Huang Z, Zhao T (2024) Neural network-based Conversion loss Model with Hard constraints for Energy Management. IEEE Trans Ind Appl 60(2):2588–2600
23. El-Bahay MH, Lotfy ME, El-Hameed MA (2023) Computational methods to mitigate the effect of high penetration of renewable energy sources on power system frequency regulation: a Comprehensive Review. Archives of Computational Methods in Engineering, 30(1):703–726.
24. Zhu D, Cheng W, Duan J, Wang H, Bai J (2023) Identifying and assessing risk of cascading failure sequence in AC/DC hybrid power grid based on non-cooperative game theory, Reliability Engineering & System Safety, 237, 109359.
25. Graber G, Calderaro V, Galdi V, Ippolito L, Massa G (2022) Impact Assessment of Energy Storage Systems supporting DC railways on AC Power Grids. IEEE Access 10:10783–10798
26. Enshasy H, Al-Haija QA, Al-Amri H, Al-Nashri M, Al-Muhaisen S (2019) A Schematic Design of HHO Cell as Green Energy Storage. Acta Electronica Malaysia 3(2):09–15
27. Zhou Z, Liu Z, Su H, Zhang L (2022) Intelligent Path Planning Strategy for Electric Vehicles Combined with Urban Electrified Transportation Network and Power Grid. IEEE Syst J 16(2):2437–2447
28. Falconer T, Mones L (2023) Leveraging Power Grid Topology in Machine Learning assisted Optimal Power Flow. IEEE Trans Power Syst 38(3):2234–2246
29. Zhang X et al (2024) Mitigating cascading failure in power grids with deep reinforcement learning-based remedial actions. Reliab Eng Syst Saf, 250, 110242.
30. Qian T et al (2022) N-1 static security assessment method for power grids with high penetration rate of renewable energy generation. Electr Power Syst Res, 211, 108200.
31. Henka N, Francois Q, Tazi S, Ruiz M, Panciatici P (2022) Power grid segmentation for local topological controllers. Electr Power Syst Res, 213, 108302.

Publisher's note