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Research on collaborative scheduling and path planning of charging pile groups using graph attention network

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Abstract

INTRODUCTION: The uneven spatiotemporal distribution of electric vehicle (EV) charging demand and the limitations of traditional methods in adapting to dynamic correlations pose significant challenges to charging infrastructure management.
OBJECTIVES: This study aims to propose a collaborative scheduling and path planning method for charging pile groups to optimize system efficiency, reduce user waiting time, lower costs, and balance grid load.
METHODS: A spatiotemporal heterogeneous graph integrating charging station states, road networks, and grid conditions is constructed. A Graph Attention Network (GAT) with a multi-head attention mechanism is employed to dynamically capture node correlations. A joint optimization model for scheduling and path planning is established, utilizing an extended A* search algorithm within a multi-objective framework.
RESULTS: Experimental results demonstrate that, compared to the Constant Power Method (CPM) and a traditional Graph Convolutional Network (GCN) method, the proposed GAT-based method reduces average user waiting time by 30-40%, decreases total system cost by 17.9%, improves the load balancing index to 0.45, reduces grid load variance by 42.4%, and successfully serves 1038 EVs.
CONCLUSION: The proposed method effectively addresses the collaborative optimization of charging pile group resources, providing an innovative solution for building an efficient and stable EV charging network.

Keywords: graph attention network, collaborative scheduling, Electric vehicle, path planning, load balancing, Grid optimization

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1. Introduction

As the global energy transition continues to accelerate and the goal of carbon neutrality continues to advance, electric vehicles are ushering in large-scale popularization as the core carrier of the clean transportation system [1-2]. However, the rapid growth of the number of electric vehicles also poses severe challenges to urban energy infrastructure, especially the uneven spatial and temporal distribution of charging pile resources and the dynamic fluctuations of user charging demand [3]. In the absence of effective scheduling strategies, user charging behavior often shows a high degree of randomness and centralization, which can easily lead to long-term overload operation of some charging stations and low utilization rate of other stations, which not only exacerbates user waiting time and increases electricity costs, but also may lead to local grid load exceeding the limit and threatening power supply security[4-5]. Therefore, how to realize the collaborative optimization of charging pile group resources and the intelligent planning of electric vehicle charging paths has become a key topic to promote the healthy development of the electric vehicle industry and build a new power system [6].

At present, the research on charging pile group scheduling and path planning mainly focuses on traditional optimization methods and classical machine learning models [7-8]. At the level of optimization methods, mathematical programming methods such as hybrid integer linear programming and dynamic programming are widely used to model charging scheduling problems, which can obtain accurate or approximate solutions under specific constraints, but generally face the limitations of high computational complexity and difficulty in adapting to large-scale real-time scenarios[9]. At the machine learning level, the method based on graph convolutional network preliminarily explores the modeling of spatial correlation between charging stations and improves the prediction and decision-making performance through neighborhood information aggregation [10]. However, such methods usually rely on fixed graph structures or predefined adjacency relationships and cannot effectively capture the differences in dynamically changing spatial dependencies and interaction intensity between nodes. In addition, most of the existing studies regard scheduling and route planning as independent issues, and fail to fully consider the multi-subject synergy mechanism of vehicle-station-network, and there is still a lot of room for improvement in the overall efficiency and robustness of the system[11-13].

In order to overcome the above challenges, this study proposes an integrated framework for collaborative scheduling and path planning of charging pile groups based on graph attention network. As a cutting-edge evolution of graph neural network, graph attention network can accurately characterize the dynamic coupling characteristics of charging station networks in the spatiotemporal dimension by introducing attention mechanisms to realize adaptive learning of the correlation strength between different nodes in the graph. This paper aims to build an end-to-end intelligent decision-making system using this technology, and the core research content covers the following aspects: firstly, a graph structure data representation method that integrates multi-source information is designed to model the state of charging stations, road networks, electric vehicles and power grids into spatial-temporal heterogeneous diagrams; Secondly, a graph neural network model based on the multi-head attention mechanism is constructed to deeply explore the spatial-temporal correlation law of multi-dimensional features such as charging station load, traffic flow, and electricity price signal. Furthermore, a joint optimization model of collaborative scheduling and path planning is established to achieve the goal of minimizing the total cost of the system under the premise of meeting the changing needs of users and the safety constraints of the power grid. Finally, large-scale simulation experiments verify the comprehensive effectiveness of the proposed method in reducing user waiting time, optimizing charging costs, improving load balancing and ensuring the stable operation of the power grid.

The main contribution of this study is to innovatively introduce the graph attention mechanism into the field of collaborative scheduling of charging pile groups, break through the dependence of traditional methods on fixed graph structures, and realize the fine modeling of complex spatial-temporal dynamic associations. The proposed system framework can not only generate personalized and efficient charging paths for each electric vehicle, but also optimize the power distribution strategy of charging pile groups from a global perspective, and provide theoretical support and technical paths for building an intelligent, efficient and robust urban electric vehicle charging service network.

2. Basic algorithm of collaborative scheduling and path planning

2.1. Graph neural network

A graph is a data structure that models a set of objects and their relationships between them. With its powerful ability to express various systems in reality, the research direction of using machine learning and deep learning methods to analyze graph structure data has attracted more and more attention, and related research spans many fields such as social sciences, natural sciences, and knowledge graphs [14]. Among them, node classification, link prediction and clustering are all mainstream directions of graph analysis research. Because graph data presents non-Euclidean characteristics, it is completely different from the Euclidean data structure of traditional text and images, and the deep learning methods that have achieved excellent results in many fields in the past decade cannot be directly applied to graph structure data[15-16]. Therefore, how to adapt deep learning technology to the data and tasks of graph structure has attracted widespread attention and has become one of the hot research topics in recent years [17].

For graphs with variable topology, a general approach to processing structural information is required. In order to ensure universal applicability, graph structure information processing methods must be designed without a known fixed causal hypothesis. The treatment of local representation solves this problem by building models at the node level rather than the full graph, which only cares about the relationships between nodes and their vicinity [18]. This processing can greatly reduce the number of parameters required for the model, similar to how CNN convolutional kernels are reused on pixels, and the processing of local representation can also be reused on all nodes, allowing for efficient combination of the "experience" of all nodes and graphs in the dataset to learn individual functions. Despite these advantages, local representation does not by itself solve the structural representation problem of variable neighborhood diagrams, as there is no consistent way to order nodes in a neighborhood. A common solution to this situation is to use a displacement invariant function (Equation 1 [19-20]) as the neighborhood information traverses for each node, and the output of the displacement invariant function does not change with changes in the order of the input elements. Because of this feature, it is ideal for handling any number of input elements, which will come in handy when dealing with topological variable disordered and non-positional graphs.

$$\Psi(Z)=\phi\left(\sum_{z\in Z}\psi(z)\right). \tag{1}$$

For graphs with cyclic relationships, it is necessary to deal with the mutual causal relationship between node states. Under the local processing assumption, the intermediate state of any node in the graph is a function of its neighbor state. When node state is computed in parallel, cyclic structural dependencies are transformed into intercausal dependencies, triggering potentially infinite loops. This problem can be solved by setting the iteration scheme to use nodes and calculate the state vl+1 at +1 iteration to calculate the state vl+1 from the lth iteration.

Context diffusion is arguably the most important concept in local graph learning methods. As the name suggests, the goal of context diffusion is to disseminate information across the graph, providing nodes with knowledge about them in a wider context rather than being limited to their immediate neighborhood, so that node feature representations can be better generated.

According to different context diffusion mechanisms, most graph learning models can be divided into three types of architecture: loop, feedforward and constructive. The Recurrent Architectures model regards the iterative processing of node information as a dynamic process, and the representative models of this type of model are graph neural networks [21-22] and graph echo state networks [23], which use single-layer loop units to model the interdependencies between node states to process graph loops by constraining the dynamic convergence process of the model. Among them, graph neural network is the earliest semi-supervised deep learning method for graph data.

Instead of an iterative diffusion mechanism on the same layer of a recursive unit, the feedforward architecture model stacks multiple layers to form a local context that learns in each iteration, and the interdependencies caused by loops are managed through layers with different parameters without constraints on the coding process to guarantee convergence. The feedforward architecture model is popular for its simplicity and efficiency on many tasks. However, deep graph neural networks face gradient-related problems such as gradient disappearance and gradient explosion as other deep neural networks, especially when learning is done "end-to-end" throughout the architecture [24].

Constructive architecture models can be regarded as special cases of feedforward models, with representative models. The constructive architecture model constructs a deep learning model framework that can process graph structure data by recursively and repeatedly combining some basic computing units such as convolution and attention. The main benefit of this architecture is that the deep network does not cause vanishing/exploding gradient issues due to design, so context can be better propagated between nodes. In addition, another important feature of this architecture is the "divide and conquer" approach to solving problems, gradually splitting tasks into simpler subtasks and thus relaxing, solving a sub-problem at one level, and gradually solving the global task using the results of the previous layer. The core of local graph processing is to aggregate the neighborhood of the target node to compute the node representation [25-26]. Following the general assumption that the nodes in the graph are out of order, a displacement invariant function needs to be used to implement the aggregation process. The neighborhood aggregation function of node v at the L+1 layer can be expressed as:

$$\mathbf{h}_v^{\ell+1} = \phi^{\ell+1}\left(\mathbf{h}_v^{\ell}, \Psi\left(\left\{\psi^{\ell+1}\left(\mathbf{h}_u^{\ell}\right) \mid u \in \mathsf{N}_v\right\}\right)\right). \quad (2)$$

Field N It can be open or closed, Ψ represents the substitution invariant function, $\ell = 0$ Corresponding to node feature x, some kind of nonlinear transformation that does not depend on structural information. For example, the neighborhood aggregation function in a graph convolutional network can be expressed as:

$$\mathbf{h}_v^{\ell+1} = \sigma\left(\mathbf{W}^{\ell+1} \sum_{u \in \mathsf{N}(v)} \mathbf{L}_{uv} \mathbf{h}_{uu}^{\ell}\right). \quad (3)$$

where L is the normalized Laplacian operator, W is the weight matrix, and σ is the nonlinear activation function.

The general neighborhood aggregation scheme mentioned above requires edges to be non-attributed or belong to the same property, which is usually not true, because the edges of the graph most often contain information, which can be discrete or continuous [27]. Therefore, we need to use the properties of edges to enrich the mechanism of node representation [28]. We can reconstruct the neighborhood aggregation function according to the label ck of the edge, and the set A of the neighborhood edge corresponds to Equation 4 for the finite and discrete case, and the corresponding formula for the continuous case is Equation 5, as follows:

$$\mathbf{h}_v^{\ell+1} = \phi^{\ell+1}\left(\mathbf{h}_v^{\ell}, \sum_{c_k \in \mathsf{A}}\left(\Psi\left(\left\{\psi^{\ell+1}\left(\mathbf{h}_u^{\ell}\right) \mid u \in \mathsf{N}_v^{c_k}\right\}\right) * w_{c_k}\right)\right). \quad (4)$$

$$\mathbf{h}_v^{\ell+1} = \phi^{\ell+1}\left(\mathbf{h}_v^{\ell}, \Psi\left(\left\{e^{\ell+1}\left(\mathbf{a}_{uv}\right)^T \psi^{\ell+1}\left(\mathbf{h}_u^{\ell}\right) \mid u \in \mathsf{N}_v\right\}\right)\right). \quad (5)$$

For cases where the edge labels are continuous, e in the formula can be any function.

The basic idea of graph neural network is to iteratively update the representation of nodes by aggregating neighbor nodes and their own representations.

$$a_v^k = \text{Aggregate}^k\left\{H_u^{k-1} : u \in N(v)\right\}. \quad (6)$$

$$H_v^k = \text{Combine}^k\left\{H_v^{k-1}, a_v^k\right\}. \quad (7)$$

Compared with traffic energy consumption data under normal conditions, charging demand data on icy and snowy roads exhibits stronger volatility and uncertainty, mainly reflected in the following aspects:

Under extreme weather conditions such as snowfall and icing, the travel behavior of electric vehicles is significantly affected. For example, during heavy snowfall, some vehicles are forced to suspend or delay travel, resulting in a noticeable drop in the demand curve; conversely, after road clearance, concentrated travel often leads to a sudden surge in demand.

In icy and snowy conditions, vehicle energy consumption depends not only on travel distance but also on factors such as the road surface friction coefficient and battery performance degradation under low-temperature conditions. These factors cause significant short-term fluctuations in demand data, presenting non-stationary characteristics [29-30].

In actual observed data, traffic sensors may be affected by snow cover or meteorological interference, leading to abnormal values; additionally, packet loss at some sampling points further increases the noise content in the data [31-32].

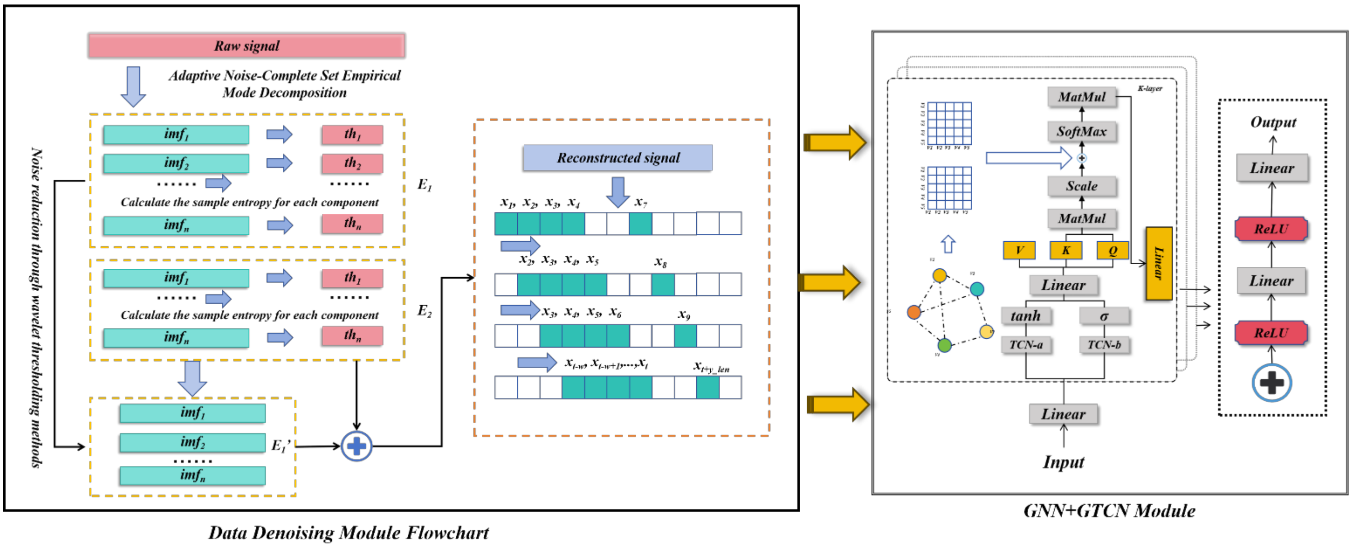

Figure 1. Schematic diagram of graph attention network module

As shown in figure 1, the AGNN module integrates a graph neural network with a multi-head attention mechanism. In the Graphometry model, three types of encoding are employed: centrality encoding, spatial encoding, and edge encoding. These encodings fully capture the spatial structural features of graphs [33]. Edge encoding and spatial encoding are embedded into the computations of the multi-head attention mechanism, while centrality encoding is incorporated into the input features of graph nodes. By embedding these encodings, the graph neural network enhanced with multi-head attention is able to effectively extract spatial features between electric vehicle (EV) charging stations, thereby optimizing the performance of the GNN in spatial information representation.

2.2. Graph Neural Network Improvement: Graph Attention Network

As an important variant of graph neural network, graph attention network realizes the differentiated processing of different neighbor nodes in the graph by introducing attention mechanism, so as to improve the expression ability of node representation. In the problem of collaborative scheduling of charging pile groups, the spatial correlation between charging stations and the temporal dependence of vehicle paths constitute a complex spatial-temporal graph structure, and the traditional graph convolutional network is difficult to adapt to the dynamically changing traffic and charging needs due to its fixed neighborhood aggregation weight. By calculating the attention weight between nodes, the graph attention network can adaptively capture the information of key nodes in the graph, thereby improving the representation ability and generalization performance of the model.

Set up the nodes in the diagram v_i is represented as $\mathbf{h}_i \in \mathbb{R}^F$, and its neighbor node set is $\mathrm{N}(i)$. Graph attention network through attention coefficient e_{ij} Measurement nodes v_i and v_j The correlation strength is calculated as:

$$e_{ij} = \text{LeakyReLU}\left(\mathbf{a}^{\top}\left[\mathbf{Wh}_i \| \mathbf{Wh}_j\right]\right). \tag{8}$$

thereinto $\mathbf{W} \in \mathbb{R}^{F' \times F}$ For the learnable weight matrix, $\mathbf{a} \in \mathbb{R}^{2F'}$ $\|$ represents vector splicing operations,LeakyReLU is an activation function. Then, the attention weight is obtained by normalizing the attention coefficient of the neighbor node α_{ij} :

$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k \in \mathrm{N}(i)} \exp\left(e_{ik}\right)}. \tag{9}$$

node v_i The updated feature is represented as the weighted sum of all neighbor node characteristics:

$$\mathbf{h}_i' = \sigma\left(\sum_{j \in \mathrm{N}(i)} \alpha_{ij} \mathbf{Wh}_j\right). \tag{10}$$

To enhance the model's expression capabilities, graph attention networks usually use a multi-head attention mechanism to splice or average the outputs of multiple attention heads:

$$\mathbf{h}_i^{'} = \|_{k=1}^{K} \sigma\left(\sum_{j \in \mathrm{N}(i)} \alpha_{ij}^{k} \mathbf{W}^{k} \mathbf{h}_j \right). \tag{11}$$

$$\mathbf{h}_i^{'} = \sigma\left(\frac{1}{K} \sum_{k=1}^{K} \sum_{j \in \mathrm{N}(i)} \alpha_{ij}^{k} \mathbf{W}^{k} \mathbf{h}_j \right). \tag{12}$$

In the problem of collaborative scheduling of charging pile groups, the graph attention network can dynamically adjust the influence weights between nodes according to the real-time traffic status, charging demand and grid load, so as to realize the effective coordination of charging station load and path planning. In addition, by introducing spatial coding and edge attribute coding, the graph attention network can further capture the spatial distance and road connectivity between charging stations and provide more accurate input features for path planning.

2.3. Algorithm training

In order to verify the effectiveness of graph attention network in the collaborative scheduling and path planning of charging pile groups, a large-scale simulation dataset based on real traffic and charging behavior was constructed. The dataset covers information such as urban road networks, electric vehicle trajectories, charging station distribution and real-time electricity prices, including 30-day operation data of 15 charging stations and 1,000 electric vehicles. During the training process, the mean square error is used as the loss function, and the model parameters are updated using the Adam optimizer, the learning rate is set to 0.001, the batch size is 32, and the number of training rounds is 200. Figure 2 shows the basic information statistics of some charging stations in the training center. The average number of charging vehicles per day reflects the service scale of the charging station, and the average charging duration and average charging power reflect the timing characteristics of charging behavior. Peak and valley loads reveal load fluctuations in the charging station throughout the day, and the load fluctuation coefficient is used to quantify load instability. It can be seen from the table that there are significant differences in load characteristics between different charging stations, which provides rich learning samples for graph attention networks, allowing them to capture the scheduling patterns in different scenarios.

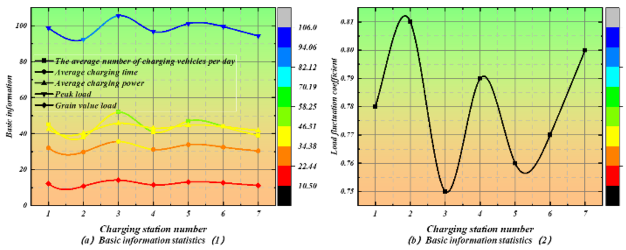

Figure 2. Statistics of basic information of charging stations in training sets

Table 1 summarizes the charging behavior data of electric vehicles in the training set. The average daily mileage and charging demand reflect the energy consumption characteristics of the vehicle, and the charging start and end time reflects the user's charging time preference. Charging frequency and average waiting time reveal the efficiency of charging services, and charging costs are directly related to the economic burden of users. These behavioral data provide an important basis for the optimization of route planning and scheduling strategies.

Table 1. Statistics of electric vehicle charging behavior in training set

Vehicle number	Average daily mileage (km)	Charging start time	Charging end time	Charging requirements(kWh)	Charging frequency(times/day)	Average wait time(min)	Charging costs (CNY)
1	85.6	08:15	09:45	35.2	1.2	5.3	12.8
2	72.3	07:30	08:50	28.7	1.5	4.8	10.5
3	91.4	18:20	20:10	42.1	1.1	6.2	15.3
4	68.9	12:10	13:40	26.8	1.8	3.9	9.7
5	79.2	09:50	11:20	32.5	1.4	5.1	11.9
6	88.1	17:40	19:30	38.7	1.3	5.8	14.2
7	75.6	14:20	15:50	30.4	1.6	4.5	10.8

Figure 3 shows the characteristic statistics of the training centralized road network. The length of the road section, the average speed and the traffic flow directly affect the traffic time and energy consumption of vehicles, and the congestion index is used to quantify the traffic efficiency of the road. The energy consumption coefficient and slope further reflect the degree of influence of road sections on the energy consumption of electric vehicles. These road features provide important input parameters for the path planning algorithm, ensuring that the planning results meet both time constraints and energy efficiency.

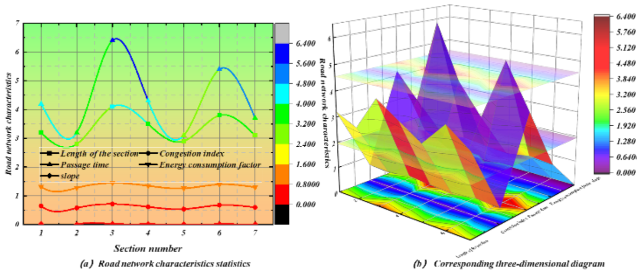

Figure 3. Statistics of road network characteristics in training set

Figure 4 shows the timing characteristics of training centralized grid loads. The load mean and variance reflect the basic operation state of the power grid, while the peak load and trough load reveal the load fluctuation of the power grid. Load growth rate and volatility are used to quantify the dynamic characteristics of load changes, and electricity prices are directly related to the calculation of charging costs. These timing features provide important grid-side inputs for collaborative scheduling algorithms, ensuring that the scheduling strategy meets charging needs while taking into account the stable operation of the grid.

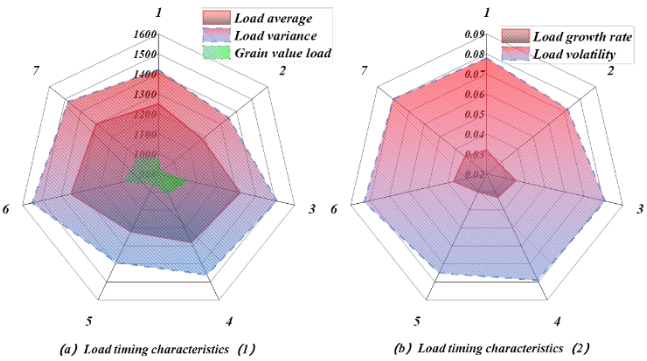

Figure 4. Training grid load timing characteristics

Figure 5 shows the statistics of the path planning results in the training set. The length of the path, the travel time and the total energy consumption reflect the physical characteristics of the path, while the number of charges, the total charging time and the total waiting time reflect the efficiency of the charging service. The total cost is used as the optimization goal, which combines time cost, energy consumption cost and charging cost. It can be seen from the figure that there is a trade-off relationship between multiple indicators in the path planning results, which provides an important reference for the design of multi-objective optimization algorithm.

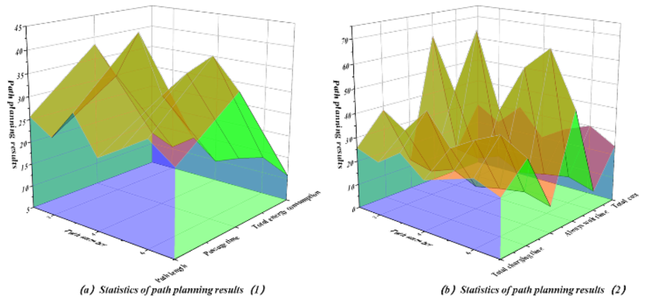

Figure 5. Statistics of path planning results of training sets

3. Collaborative scheduling and path planning system for charging pile groups

3.1. Overall system framework and data generation module

The overall framework of the charging pile group collaborative scheduling and path planning system proposed in this study aims to realize the collaborative management of multiple charging stations in the region and the intelligent path guidance of electric vehicles through integrated information processing and decision-making optimization [37]. The core of the system is composed of a data generation module, a path planning simulation module, a graph attention network modeling module and an optimization decision module, forming a closed-loop intelligent decision-making system, as shown in Figure 6. The data generation module is responsible for providing real and reliable training and testing data for the system, which simulates and generates the travel trajectory, charging demand and dynamic traffic status of electric vehicles based on large-scale traffic survey data and urban road network information. The path planning simulation module calculates the optimal driving path and charging options for electric vehicles based on real-time traffic information and charging station status. The graph attention network modeling module is the intelligent center of the whole system, which provides key feature representation for collaborative scheduling by modeling the spatial dependencies and temporal dynamic characteristics of the charging station network [38]. The optimization decision module finally synthesizes various information, and outputs the optimal charging scheduling and path planning strategy with the goal of minimizing the total cost of the system.

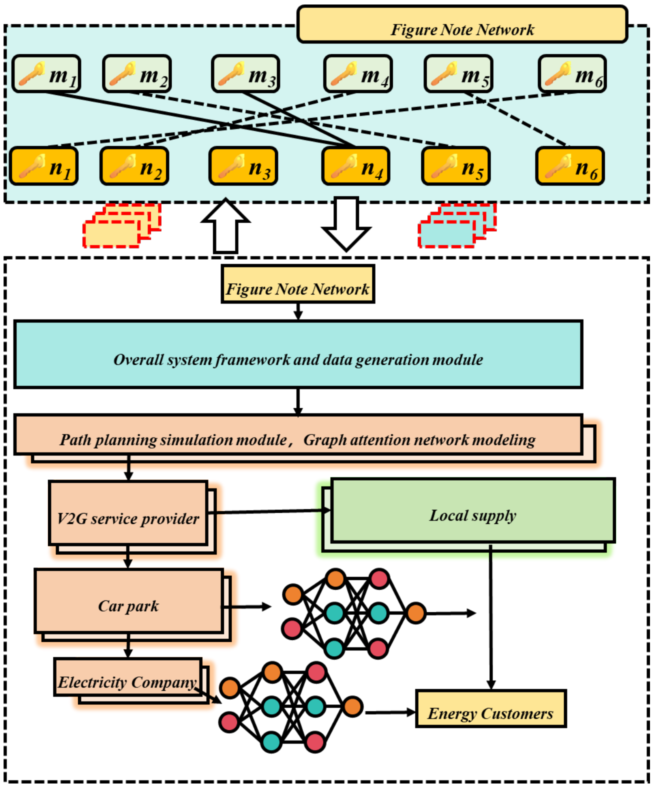

Figure 6. Model frame diagram

In the Data Generation module, the key step lies in building datasets that reflect real-world complexities. We define the urban road network as a graph structure:

$$G_r = (V_r, E_r) \tag{13}$$

thereinto V_r Representative intersection gathering, E_r Representative section gathering. Each section $e \in E_r$ Give a set of attributes, including length l_e Baseline travel time t_e^0, dynamic passage time $t_e(t)$ and the passing energy consumption coefficient γ_e. The travel chain of an electric vehicle is represented by a sequence:

$$T_v = \{o_v, d_v, E_v^{\text{req}}, T_v^{\text{arr}}, T_v^{\text{dep}}\}. \tag{14}$$

thereinto o_v and d_v Origin and destination respectively, E_v^{req} For charging needs, T_v^{arr} Represents a charging station, the attributes of which include the number of charging piles N_i^{pile}, rated power P_i^{rate} It can be defined as the minimum path distance or travel time between two stations.

In order to simulate dynamic traffic conditions, the module introduces the time-varying traffic time function. One widely used model is a traffic-dependent function, such as the Federal Highway Administration's BPR function:

$$t_e(f_e(t)) = t_e^0\left[1 + \alpha\left(f_e(t)/C_e\right)^{\beta}\right]. \tag{15}$$

thereinto $f_e(t)$ It is the traffic flow on the road at all times. C_e is the road section capacity,α and β is the calibration parameter. The energy consumption model of an electric vehicle takes into account factors such as road slopes and average speed, and is defined as:

$$E_v^{cons}(e) = \gamma_e l_e + \eta_v \cdot \Delta h_e. \tag{16}$$

thereinto γ_e is the energy consumption factor per unit distance, η_v is the vehicle-related slope influence factor, Δh_e is the elevation change of the road section. By integrating road networks, vehicle travel chains, charging station attributes, and dynamic traffic flow, the data generation module can batch synthesize multi-scenario datasets with spatiotemporal consistency, providing a solid foundation for subsequent model training and verification. The overall logical flow of the module is designed to ensure that the generated data covers both normal traffic patterns and extreme situations such as traffic congestion or charging station failures, thereby comprehensively testing the robustness and adaptability of the system.

3.2. Path planning simulation module

The goal is to calculate an optimal path for each electric vehicle requested from the starting point to the destination, which may include a midway charging station, under the premise of meeting the changing needs of users, comprehensively considering multiple factors such as driving time, charging cost, waiting time and grid load. The module runs based on real-time updated traffic information and charging station status and adopts a simulation framework that integrates graph search and multi-objective optimization [39]. The module's input includes real-time status of electric vehicles, dynamic traffic conditions of the road network, real-time availability of charging stations, and electricity price information. The output is a detailed path sequence indicating the route, the charging station selected, the estimated charging time, and the total cost estimate.

The core algorithm of the module is based on an extended A* search algorithm, which explores paths containing charging behavior by introducing charging station nodes as possible stopover points in the search graph. The defined state space is (n, e, t)

where, n represents the current node position, he represents the remaining power of the vehicle, and t represents the current moment. From the state (n, e, t) transfer to the cost function of the adjacent node n $c(n, n')$ Including time and energy costs:

$$c(n, n') = \lambda_{\text{time}} \cdot t_{n,n'}(t) + \lambda_{\text{energy}} \cdot E_{n,n'}^{\text{cons}}. \tag{17}$$

thereinto $t_{n,n'}(t)$ is the dynamic travel time, $E_{n,n'}^{\text{cons}}$ energy consumption of road sections, λ_{time} and λ_{energy} is the weight coefficient. If the vehicle reaches the charging station node s and the remaining charge is below the safe threshold, the charging behavior is triggered. Charging time at the charging station $T_v^{ch}(s)$ Depends on the amount of charge required ΔE_v and charging pile power P_s^{rate} :

$$T_v^{ch}(s) = \Delta E_v / P_s^{rate} \cdot \tag{18}$$

thereinto η^{ch} for charging efficiency. The cost of charging is:

$$\text{Cost}^{ch}(s) = C_s^{elec}(t) \cdot \Delta E_v \cdot \tag{19}$$

In addition, the module must take into account the waiting time in line at the charging station. Suppose the service process of the charging station s obeys the M/M/C queuing model, and its current queue waiting time $W_s(t)$ Available based on arrival rate $\lambda_s(t)$ and service rate μ_s Make an estimate:

$$W_s(t) \approx \frac{\left(\lambda_s(t)/\mu_s\right)^{N^{st}}}{N_s^{st/1} N_s^{st/e} \mu_s \left(1-\rho_s(t)\right)^2} P_0 \quad . \tag{20}$$

thereinto $\rho_s(t) = \lambda_s(t) / \left(N_s^{\text{pile}} \mu_s\right)$ For service intensity, P_0 is the probability of system idleness. Hence the total time spent at the charging station s $T_v^{\text{stay}}(s)$ For the sum of the waiting time and charging time:

$$W_s(t) \approx \frac{\left(\lambda_s(t)/\mu_s\right)^{N^{st}}}{N_s^{st/1} N_s^{st/e} \mu_s \left(1-\rho_s(t)\right)^2} P_0 \quad . \tag{21}$$

The total cost function of the path F_{tatal} is formalized as a multi-objective weighted sum:

$$F_{\text{total}} = \lambda_t T_{\text{travel}} + \lambda_c Cost_{ch} + \lambda_w T_{\text{wait}} + \lambda_g P_{\text{grid}} \cdot \tag{22}$$

thereinto T_{travel} is the total travel time, $Cost_{ch}$ For the total charging cost, T_{wait} is the total waiting time, P_{grid} In order to reduce the load impact on the power grid, $\lambda_t, \lambda_c, \lambda_w, \lambda_g$ is the corresponding normalized weight coefficient. By executing this optimization process in real time, the path planning simulation module can provide dynamic, personalized and system-friendly charging path suggestions for electric vehicles, which is a key technical link to realize vehicle-station-network collaboration.

3.3. Path planning simulation module

In this system, the collaborative scheduling problem of charging pile group is naturally modeled on a graph structure, where the nodes represent the charging stations and the edges represent the geographical or functional associations between the stations. In order to effectively capture the complex and dynamic spatial dependencies between charging stations and generate optimal scheduling strategies accordingly, we use graph attention networks for modeling. The modeling process mainly includes three core parts: node feature construction, attention mechanism design, and constraint modeling.

Node feature construction is the basis of the model. per charging station node v_i The eigenvector at the time step h_i^t Its state needs to be fully characterized. The feature vector we construct contains static and dynamic properties:

$$\text{h}_i^t = \left[N_i^{\text{pile}}, Pr_i^{\text{rate}}, C_i^{\text{base}}, \text{h}_i^{\text{dym}}(t)\right] \cdot \tag{23}$$

Among them, the first three are static characteristics, representing the number of charging piles, rated power and basic electricity price. Dynamic features

$\text{h}_i^{dyn}(t)$ is a multivariate time series containing real-time information:

$$\mathbf{h}_i^{\text{dym}}(t) = \left[Q_i(t), U_i(t), C_i^{\text{elec}}(t), L_i^{\text{grid}}(t)\right] \cdot \tag{24}$$

Over here $Q_i(t)$ is the number of vehicles in queue, the average utilization rate of charging piles:

$$U_i(t) = \frac{\sum_{i1}^{N_i^{\text{ple}}} P_i(t)}{N_i^{\text{de}} \cdot P_i^{\text{det}}} . \tag{25}$$

$C_i^{\text{elec}}(t)$ is the real-time electricity price, $L_i^{\text{grid}}(t)$ The total power that the station gets from the grid. By integrating dynamic and static characteristics, node representation can accurately reflect the real-time operation status and resource endowment of charging stations.

Attention mechanism design is the core of the model and is used to learn the intensity of interaction between nodes. We take a multi-headed graph attention layer. First, the node features undergo a shared linear transformation:

$$\text{z}_i^l = \text{W}^l \text{h}_i^l \cdot \tag{26}$$

thereinto W^l is the trainable weight matrix of the l-layer. Next, node I and its neighbors are calculated $j \in \mathrm{N}(i)$ Attention score between e_{ij}^l :

$$e_{ij}^l = LeakyReLU\left(\text{a}^{\cdot} \left[\text{z}_i^l \| \text{z}_j^l\right]\right) \cdot \tag{27}$$

Among them, ‖ represents vector splicing, $\mathbf{a}^l$ which is a trainable parameter vector of attention mechanism. Then, the attention score is normalized using the SoftMax function to obtain the attention weight α_{ij}^l:

$$\alpha_{ij}^l = \frac{\exp\left(e_{ij}^l\right)}{\sum_{\tan(j)} \exp\left(e_{ij}^l\right)} \quad . \tag{28}$$

The output of each attention head is the weighted sum of the neighbor's node features:

$$\mathbf{h}_i^l = \sigma\left(\sum_{j\in N(i)} \alpha_{ij}^l z_j^l\right). \tag{29}$$

By stacking such networks with multiple layers, the model is able to capture dependencies over longer distances.

Constraint modeling ensures that the model output conforms to physical and reality rules. These constraints are achieved through penalty terms in loss functions or post-processing of network outputs. Charging power constraints require that the power allocated to each charging station does not exceed its total capacity:

$$\sum_{v\in V} P_v^{ch}(t) \le N_i^{pile}. \tag{30}$$

thereinto $\forall i,t$ It is a collection of vehicles charged at Station I. Grid safety constraints limit the total load of a substation or line:

$$\sum_{i\in S_b} L_i^{grid}(t) \le L_b^{\max}(t). \tag{31}$$

thereinto S_b is a collection of charging stations connected to grid node B, $L_b^{\max}(t)$ is the maximum allowable load for that node. Vehicle charging demand constraints ensure that the vehicle reaches the desired level of power before leaving:

$$SOC_v\left(T_v^{\text{dep}}\right) \ge SOC_v^{\text{target}}. \tag{32}$$

These constraints are integrated into the model's optimization objectives, such as through the Varangian multiplier method or the projection gradient method, ensuring that the scheduling scheme generated by the graph attention network is not only efficient but also feasible and secure.

4. Simulation analysis of experimental examples

In order to verify the effectiveness and superiority of the charging pile group collaborative scheduling and path planning system based on graph attention network proposed in this study, a comprehensive experimental example is designed for simulation analysis. The experiment is based on a simulated urban transportation network and charging station network, which contains the daily travel data of 50 traffic nodes, 15 charging stations and 1000 electric vehicles. We will compare this method (GAT-CSP) with two benchmark methods, namely constant power scheduling method (CPM) and traditional graph convolutional network scheduling method (GCN-CSP), from three dimensions: charging station vehicle arrival timing, path planning and scheduling effect, charging cost and grid load.

4.1. Analysis of the arrival timing of charging station vehicles

An in-depth analysis of the timing law of electric vehicles arriving at charging stations is the basis for evaluating the ability of scheduling strategies to cope with tidal effects. We counted the distribution of vehicle arrivals at all charging stations in a typical 24-hour working day.

Figure 7 shows the spatial-temporal inhomogeneity of the arrival of vehicles at each charging station. The charging station S04 has a high arrival volume at all times of the day, with a total of 240 vehicles per day, which may be located in transportation hubs or commercial centers. The S01 and S07 arrived in the early morning hours (00:00-04:00) with a very low number of arrivals, with 5 and 4 vehicles respectively. All charging stations have significant peaks of arrival at 08:00-12:00 and 16:00-20:00, which is highly consistent with the morning and evening peak characteristics of urban commuting. This significant tidal phenomenon poses a challenge to scheduling strategies, requiring systems to be able to direct vehicles from peak congestion sites to relatively idle sites.

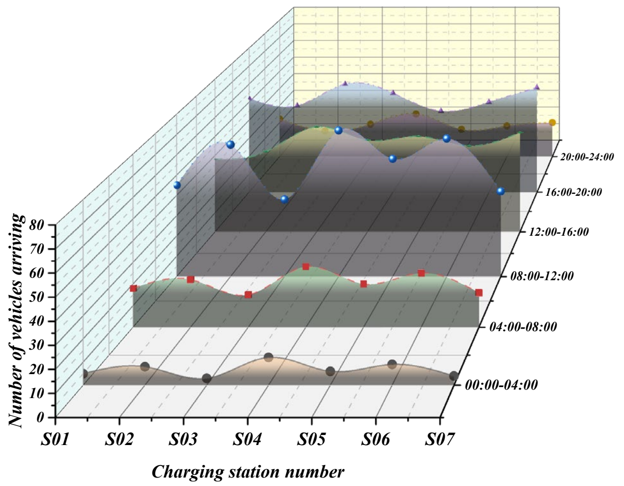

Figure 7. Statistics of the number of vehicles arriving at each charging station by time period

Table 2 further focuses on the morning rush hour (08:00-12:00), showing the dynamic load situation of each station. Arrival rate is calculated based on the number of vehicles arriving in 4 hours in Table2, assuming a constant service rate. It can be seen that the S04 site has the highest arrival rate, reaching 0.200 vehicles per minute, and has the longest initial queue length (8 vehicles), resulting in a theoretical waiting time of up to 42.8 minutes. The S03 site has a relatively light load. This reveals that there is a serious imbalance between charging stations during peak periods. An intelligent scheduling system must be able to sense this difference and optimize overall system efficiency through path guidance to avoid concentrating users to a few popular sites

Table 2. Arrival rate and initial queue length of each charging station during peak hours (08:00-12:00)

Charging station number	Arrival rate(veh/min)	Initial queue length (veh)	Average service rate(veh/min)	Theoretical waiting time(min)
S01	0.125	4	0.167	28.5
S02	0.181	6	0.167	35.2
S03	0.106	3	0.167	22.1
S04	0.200	8	0.167	42.8
S05	0.161	5	0.167	31.6
S06	0.189	7	0.167	38.9
S07	0.117	4	0.167	26.3

Figure 8 compares the differences in user experience brought about by three different scheduling methods during morning rush hours. Constant Power Scheduling CPM has the longest waiting time for users due to the lack of cooperative guidance, and the waiting time for the heaviest S04 station is more than 45 minutes. The traditional GCN-CSP method alleviates congestion to a certain extent by utilizing spatial information, reducing the average waiting time by about 15%-20% compared to CPM. The GAT-CSP method proposed in this study has the best performance, which uses the graph attention mechanism to capture the dynamic correlation between stations more finely, and achieves better load balancing, which reduces the waiting time of each station by about 30%-40% compared with the CPM, and the waiting time of S04 station is effectively controlled at 26.7 minutes. This is a preliminary demonstration of the significant advantages of GAT-CSP in improving user experience.

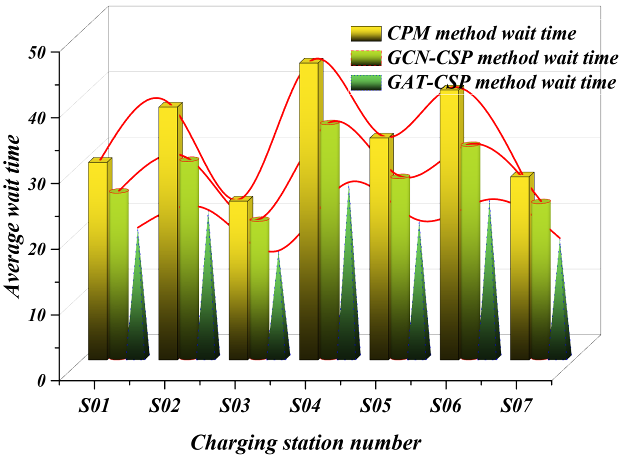

Figure 8. Comparison of average waiting time during peak hours under different scheduling methods

4.2. Comparison of path planning and scheduling effects

This subsection evaluates the combined performance of different methods on key performance indicators based on the final results of path planning. Figure 9(a) comprehensively compares the average performance of the three methods on a number of key indicators. The GAT-CSP method outperformed both benchmark methods on all indicators. In terms of efficiency, GAT-CSP achieves the lowest average travel time and waiting time, thanks to its accurate congestion prediction and route guidance. In terms of economy, it has the lowest average charging cost because it directs vehicles more intelligently to charge at stations with lower electricity prices or idleness. The highest success rate of path planning indicates that it has a stronger ability to cope with complex constraints. The average SOC boost value is higher, indicating that the vehicle has received more efficient energy replenishment during the stay. In the end, the total user satisfaction calculated by combining these indicators reached 85.4, which was significantly higher than the CPM of 72.3 and the GCN-CSP of 78.9. This indicates that GAT-CSP strikes a better balance between time, cost, and service quality. Figure 9(b) compares the performance of different methods from the perspective of the system operator. The GAT-CSP approach achieves the lowest total system cost, which is approximately 17.9% lower than the CPM. The total power consumption is also the lowest, indicating that its scheduling strategy contributes to overall energy efficiency. The load balancing index is an index to measure the load uniformity of each charging station, and the closer it is to 0, the more balanced it is, and the 0.45 of GAT-CSP is significantly better than that of 0.68 of CPM and 0.59 of GCN-CSP, which proves that its collaborative scheduling ability effectively realizes load balancing. The higher average pile utilization rate (0.82) and the total number of vehicles served (1038 vehicles) indicate that GAT-CSP can serve more users under the same infrastructure conditions, improving the asset utilization rate and overall social benefits of the charging station cluster.

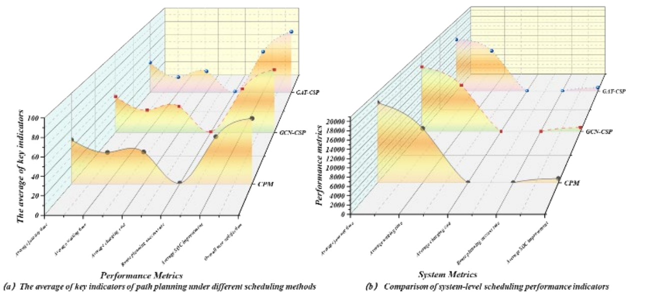

Figure 9. Impact analysis of each indicator

Figure 10 further segments of the vehicles according to the travel distance and analyzes the adaptability of the scheduling method to users with different needs. The GAT-CSP approach provides the best experience for users of all distance segments. It is worth noting that with the increase of travel distance, the gap between the indicators of the three methods tends to widen. For example, for long-distance users, GAT-CSP reduced the average time by 11.1 minutes, reduced the cost by 9.5 yuan, and increased satisfaction by 14.1 percentage points compared to CPM. This shows that GAT-CSP has a more obvious optimization effect for long-distance users with higher energy consumption and more urgent charging needs, and its collaborative scheduling strategy can better plan mid-way replenishment for such users and avoid mileage anxiety.

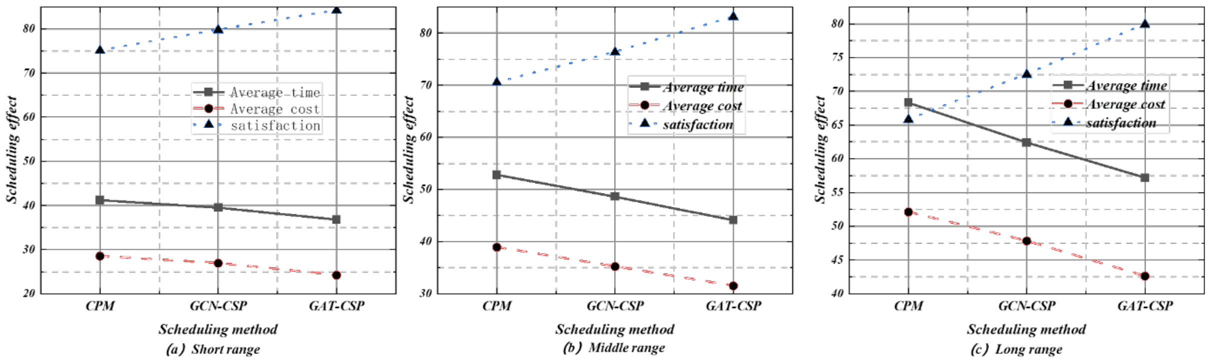

Figure 10. Comparison of vehicle scheduling effects in different travel distance segment

4.3. Charging cost and grid load analysis

This subsection focuses on the impact of the proposed method on the economy and grid security. Figure 11 reflects the influence of different scheduling methods on the peak load of the local power grid. Due to the concentration of charging behavior, the peak load of all grid nodes is at a high level, among which the load of Node6 reaches 1400kW, which is close to its capacity limit of 1450kW, which has potential safety hazards. The GCN-CSP method has been improved. The GAT-CSP method significantly reduces the peak load of each node through the optimal load allocation in time and space, and the load of all nodes is far away from its capacity limit, leaving sufficient safety margin for the power grid. This shows that the GAT-CSP method not only considers the economy of users and operators but also takes grid security as an important optimization goal, reflecting the advanced concept of vehicle-station-network collaboration.

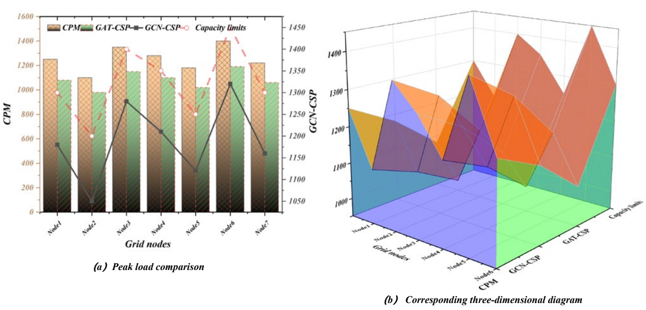

Figure 11. Comparison of peak load of power grid nodes

As shown in Figure 12(a), the GAT-CSP method achieves a grid load variance of 7200, representing a 42.4% reduction compared to the CPM method's 12500.The GAT-CSP method achieved the lowest total daily charging cost, saving about 5,760 yuan or 16.3% compared to CPM. Grid load variance is an indicator to measure the size of load fluctuations, and the smaller the variance, the more stable the load. The grid load variance of GAT-CSP is 7200, which is much lower than the CPM of 12500, which indicates that its scheduling strategy effectively smooths the total load curve of the power grid, reduces the violent power fluctuations, and is extremely beneficial to the safe and stable operation of the distribution network. Figure 12(b) explores the further potential of the GAT-CSP method after the introduction of the V2G mode. Compared with the basic scenario without V2G, passive V2G (that is, the vehicle spontaneously discharges to the grid when the electricity price is high) can bring certain benefits and reduce the net cost. The GAT-CSP collaborative V2G model achieves higher electricity sales revenue (2,200 yuan) and lower power purchase cost by centrally optimizing the charging and discharging timing sequence, further reducing the net cost to 25,000 yuan. At the same time, through the precise control of V2G power, the net load fluctuation of the power grid is reduced to 5200, which significantly improves the consumption capacity and operation stability of the power grid.

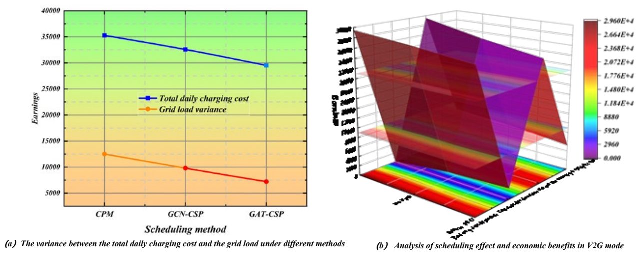

Figure 12. Variance between the total daily charging cost and the grid load under different methods

5. Conclusion

In this study, the dynamic perception and intelligent decision-making of the charging station network in the region are realized by constructing a charging pile group collaborative scheduling and path planning system based on graph attention network, using a spatial-temporal graph neural network model integrating the multi-head attention mechanism, combined with the extended A-star search algorithm and multi-objective optimization framework. In terms of research methods, the states of charging stations, road networks and power grids are innovatively modeled into spatial-temporal heterogeneous graphs, and the association strength between nodes is adaptively learned through graph attention networks, and a joint optimization model including charging power constraints, grid safety constraints and vehicle demand constraints is established. The experimental results show that:

(1)Compared with the traditional constant power scheduling method and graph convolutional network method, the proposed method achieves remarkable results in the test scenario including 50 traffic nodes, 15 charging stations and 1000 electric vehicles: the average waiting time of users is reduced by 30% to 40%, and the waiting time of the S04 station during peak hours is optimized from 45.2 minutes to 26.7 minutes.

(2)the total cost of the system was reduced by 17.9%, and the total daily charging cost was reduced by 5,760 yuan; The load balancing index increased from 0.68 to 0.45, the average utilization rate of charging piles reached 0.82, and the number of service vehicles increased to 1,038. The variance of grid load decreased by 42.4%, and the peak load of each node was stable within the safety limit.

(3)The graph attention network can effectively capture the complex spatial-temporal correlation between charging stations and achieve the dual goals of optimal allocation of charging resources and safe and stable operation of the power grid while improving user satisfaction to 85.4 points.

(4)This study successfully solves the dynamic correlation modeling problem in the collaborative scheduling of charging pile groups, provides a scalable intelligent decision-making scheme for the urban electric vehicle charging network, which has important practical value for promoting the intelligent transformation of transportation energy system, and lays the theoretical foundation and technical support for the construction of a new power system with vehicle-station-network collaboration.

While this study has achieved significant outcomes, several limitations remain and provide directions for future research. First, although the research is based on large-scale simulation data and strives to reflect real-world conditions, there is still a gap compared to the complexity and uncertainty of actual urban environments. Future work could consider collaborating with urban transportation and power grid operators to validate models using real data and fine-tune them. Second, the model requires substantial computational resources, and its real-time response performance in ultra-large urban networks needs further optimization. Future efforts could explore more lightweight network architectures or distributed computing methods. Finally, while this study primarily focuses on unidirectional charging (G2V), future research could integrate vehicle-to-grid (V2G) bidirectional energy interactions more deeply into collaborative optimization frameworks to enhance grid flexibility and economic efficiency.

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