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(Research Article)

Considering the spatiotemporal optimal scheduling strategy of electric vehicles entering the network

Xiu Wan *, Yongqi Ren and Lingxiao Wu

School of Electric Power Engineering, Nanjing Institute of Technology, Nanjing, Jiangsu, China.

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Abstract

With the intensification of the contradiction between economic development, fossil fuel shortages, and severe environmental pollution, the development and widespread adoption of Electric Vehicles (EVs) have become an inevitable trend. The large-scale and disorderly charging of EVs connected to the grid will impose significant impacts on the power system, potentially leading to local overloads and threatening the security and economic operation of the grid. Therefore, this study investigates the coordinated optimization planning problem involving generators, EVs, and renewable energy sources (wind and solar). A spatiotemporal optimization strategy for EV charging scheduling is proposed. On the temporal scale, an optimal scheduling model based on unit commitment is established, aiming to minimize the operational costs of generators on the transmission grid side, PM2.5 emissions, total user charging costs, and the curtailment of wind and solar power. On the spatial scale, an optimal power flow-based scheduling model is developed to reduce distribution network losses, taking into account network security constraints and the spatial migration characteristics of EVs. The proposed EV charging scheduling strategy is simulated and analyzed on a power system model comprising a standard 10-machine transmission network and an IEEE 33-node distribution network. The results validate the effectiveness and superiority of the proposed spatiotemporal optimization scheduling strategy.

Keywords: Electric Vehicles; Spatiotemporal Optimization Charging Strategy; Unit Commitment; Optimal Power Flow

1. Introduction

With the continuous growth in the number of electric vehicles (EVs), their spatiotemporal distribution characteristics and the convergence of user behavior patterns may lead to large-scale disordered charging, posing significant load impacts on the power grid. At the same time, wind power, as a clean and renewable energy source, has experienced rapid development, but its grid integration may introduce stability risks to the power system [1].

Existing research has primarily focused on optimizing charging strategies in low-voltage distribution network scenarios, with limited consideration for the coordinated regulation of generation units on the transmission grid side [2-3]. In the field of transmission grid coordination optimization, some scholars have established objective functions that balance the operational costs of thermal power units and carbon emissions, achieving load curve smoothing through EV charging management [4-7]. Studies have confirmed that such coordination mechanisms can not only reduce the system's reliance on small-capacity peaking units but also effectively decrease overall operational costs and carbon emissions. Notably, bi-level optimization theory has recently demonstrated unique advantages in charging scheduling. Reference [8] proposed a bi-level optimization framework considering power grid security constraints: the upper-level model addresses the unit commitment problem to determine the optimal charging capacity for each time period, while the lower-level model allocates this capacity spatially under AC power flow constraints. Although this scheme is designed for the transmission grid, its practical scheduling flexibility remains limited due to the deterministic

* Corresponding author: Xiu Wan

characteristics of EV distribution at nodes. The aforementioned EV charging strategies optimize scheduling separately in either the transmission or distribution network layers across temporal and spatial dimensions. However, as highlighted in reference [9], it is necessary to simultaneously optimize EV charging strategies in both the transmission and distribution network layers. In summary, this paper proposes a spatiotemporal optimization model-based EV charging scheduling strategy. This strategy optimizes the temporal coordination of EVs, generation units, and renewable energy sources on the transmission grid side, while considering the spatial mobility of EV charging loads on the distribution grid side. This paper assumes that EV charging behavior fully complies with grid scheduling.

2. Spatiotemporal optimization model of large-scale electric vehicles entering the network

2.1. Optimal scheduling modeling on time scale

Considering the volatility and uncertainty of wind power, this paper adopts scenario-based method to describe the volatility and uncertainty of wind power. On the transmission side, in order to coordinate the charging load of electric vehicles with the output of generator set and the wind-view output in time to achieve the optimal effect, the upper level scheduling strategy based on the day-ahead unit combination model is adopted, and its optimization variables are the start and stop state of the unit and its output, the number of electric vehicles charged, wind abandon and light power in each period. The modeling process of optimal scheduling strategy on time scale is as follows.

2.1.1. Objective function

On the time scale, the goal is to coordinate the charging load of electric vehicles on the transmission side with the output of the generator set and the scenery output, so as to improve the overall economy. Therefore, the optimization strategy on the transmission side should be able to reduce the operating cost of the generator set, reduce the emission of pollutants, increase the scenery absorption rate of new energy as much as possible, and reduce the charging cost of electric vehicle owners. Therefore, the objective function should include the fuel cost of unit operation, the cost of start-up and shutdown, the penalty cost of pollutant emission, the charging cost of the owner, and the penalty cost of abandoning the scenery.

Goal one: Fuel costs

$$C_{ost1,i}\left(P_{i,t}^{s}\right)=a_i+b_iP_{i,t}^{s}+c_iP_{i,t}^{s2}$$

In the equation: $C_{ost1,i}\left(P_{i,t}^{s}\right)$ represents the fuel cost of generating unit *i* at time period t under scenario *s*; a_i , b_i , and c_i are the coefficients of the fuel cost characteristic curve for unit *i*, and $P_{i,t}^{s}$ is the active power output of generating unit *i* at time period *t* under scenario *s*.

Goal 2: Penalty costs for pollutant emissions

$$C_{ost2,i}\left(P_{i,t}^{s}\right)=c_e[Aar\cdot\omega\cdot(1-\eta/100)\cdot(\alpha_i+\beta_iP_{i,t}^{s}+\gamma_iP_{i,t}^{s2})/10000]$$

In the equation: $C_{ost2,i}\left(P_{i,t}^{s}\right)$ represents the PM2.5 emissions of generating unit *i* at time period *t* under scenario *s*; c_e is the penalty price factor for PM2.5 emissions; *Aar* is the average ash content of coal on an as-received basis (%), with a default value of 20 in calculations; *ω* is the conversion coefficient from coal ash to PM2.5 (%), with a default value of 5.1 in calculations; *η* is the removal efficiency of control measures for PM2.5 (%), with a default value of 99 in calculations [7-8]; PM2.5 emissions are proportional to coal consumption, and α_i, β_i and γ_i are the coal consumption characteristic curve coefficients of unit *i*.

Target 3: start-stop costs

$$C_{ost3,i,t}=\begin{cases}S_i^h, \mathrm{T}_i^{\mathrm{off}}<X_{i,t}^{\mathrm{off}}\le H_i^{\mathrm{off}}\\ S_i^c, X_{i,t}^{\mathrm{off}}>H_i^{\mathrm{off}}\end{cases}$$

$$C_{ost4,t} = \mathrm{T}_i^{\mathrm{off}} + \mathrm{T}_i^c$$

In the equation: $C_{ost3,i,t}$ represents the startup cost of generating unit *i* at time period *t*; S_i^h is the hot startup cost of generating unit *i*; S_i^c is the cold startup cost of generating unit *i*; $X_{i,t}^{\mathrm{off}}$ is the continuous downtime of generating unit *i* before time period *t*; H_i^{off} is the transition time between hot startup and cold startup for unit *i*; $C_{ost4,i,t}$ is the shutdown cost of generating unit *i* at time period *t*; T_i^{off} is the minimum allowable downtime of generating unit *i*; and T_i^c is the cold startup time of generating unit *i*. In standard systems, the shutdown cost of thermal power units is typically a constant and is usually set to 0.

Target 4: User charging cost

$$C_{ost5,t}{}^{s} = c_t P_{ev,t}^s$$

In the equation: $C_{ost5,t}{}^{s}$ represents the total charging cost of EV owners at time period *t* under scenario *s*; c_t is the charging price for EVs at time period *t*, and $P_{ev,t}^s$ is the EV charging load at time period *t* under scenario *s*.

Goal six: The cost of abandoning scenery

$$C_{ost6,t}{}^{s} = \sum_{m=1}^{M_1} c_w \Delta P_{wind,m,t}^s + \sum_{n=1}^{N_1} c_{pv} \Delta P_{pv,n,t}^s$$

In the equation: $C_{ost6,t}{}^{s}$ represents the penalty cost for wind and solar curtailment at time period *t* under scenario *s*; M_1 is the number of wind farms; c_w is the penalty price for wind curtailment; $\Delta P_{wind,m,t}^s$ is the curtailed wind energy of wind farm *m* at time period *t* under scenario *s*; N_1 is the number of photovoltaic (PV) panels; c_{pv} is the penalty price for solar curtailment; and $\Delta P_{pv,n,t}^s$ is the curtailed solar energy of PV panel *n* at time period *t* under scenario *s*.

Equations (1) to (6) represent the fuel cost of generating units, the penalty cost for PM2.5 emissions, the startup cost, the shutdown cost, the user charging cost, and the cost of wind and solar curtailment, respectively. Among these, when determining the unit commitment sequence, the objective is to minimize the startup and shutdown costs of the units; when determining the operating base points of online units driven by wind power scenarios, the objective is to minimize the expected cost across all scenarios. The overall objective function can be expressed as:

$$\min\left\{\sum_{t=1}^{T}\sum_{i=1}^{N_g} C_{ost3,i,t}^s\left(1-u_{i,t-1}\right)u_{i,t} + E\left\{\sum_{s=1}^{N_s}\rho_s \sum_{t=1}^{T}[\sum_{i=1}^{N_g}\left(C_{ost1,i}\left(P_{i,t}^s\right)+C_{ost2,i}\left(P_{i,t}^s\right)\right)u_{i,t} + C_{ost5,t}^s + C_{ost6,t}^s]\right\}\right\}$$

In the equation: *T* represents the total number of optimization time periods; N_g is the total number of generating units; N_s is the number of wind and solar scenarios; $C_{ost3,i,t}$ is the startup cost function of thermal unit *i* at time period *t*; $u_{i,t}$ is the operating state of generating unit *i* at time period *t*, where 1 indicates operation and 0 indicates shutdown; $E\{\cdot\}$ denotes the mathematical expectation over all scenarios; ρ_s is the probability of occurrence of the combined wind and solar output scenario *s*; $C_{ost1,i}\left(P_{i,t}^s\right)$ is the fuel cost function of thermal unit *i*; $P_{i,t}^s$ is the active power output of generating unit *i* at time period *t* under scenario *s*; $C_{ost2,i}\left(P_{i,t}^{s}\right)$ is the PM2.5 emission penalty cost of thermal unit *i*; U_{t}^{s} is the total charging cost of EV owners at time period *t* under scenario *s*; and $C_{ost6,t}^{s}$ is the total penalty cost for wind and solar curtailment of wind farms at time period *t* under scenario *s*.

(2) Constraint conditions

The following constraints must be met at each time period t.

Power balance constraints:

$$\sum_{i=1}^{N_g}(u_{i,t}P_{i,t}^{s})+\sum_{m=1}^{M_1}(P_{wind,m,t}^{s}-\Delta P_{wind,m,t}^{s})+\sum_{n=1}^{N_1}(P_{pv,n,t}^{s}-\Delta P_{pv,n,t}^{s})=D_t+P_{ev,t}^{s}$$

In the equation: D_t represents the total base load of the system at time period *t*; $P_{wind,m,t}^{s}$ is the predicted wind power output of wind unit *m*at time period *t* under scenario *s*; and $P_{pv,n,t}^{s}$ is the predicted photovoltaic output of PV panel *n* at time period *t* under scenario *s*.

Rotation reserve constraints of the system:

$$\sum_{i=1}^{N_g}\left(u_{i,t}P_{i}^{\max}\right)+\sum_{m=1}^{M_1}(P_{wind,m,t}^{s}-\Delta P_{wind,m,t}^{s})+\sum_{n=1}^{N_1}(P_{pv,n,t}^{s}-\Delta P_{pv,n,t}^{s})\geq D_t+P_{ev,t}^{s}+R_t$$

In the equation: $P_{i}^{\max}$ represents the maximum output power of generating unit *i*; and R_t is the system spinning reserve requirement at time period *t*.

Unit output constraints:

$$P_{i}^{\min}u_{i,t}\leq P_{i,t}^{s}\leq P_{i}^{\max}u_{i,t}$$

In the equation: $P_{i}^{\min}$ is the minimum output power of generator set i.

Climbing constraints:

$$-R_{d,i}\leq P_{i,t}^{s}-P_{i,t-1}^{s}\leq R_{u,i}$$

In the equation: $R_{u,i}$ is the maximum up-regulation power of unit *i* in a single period; $R_{d,i}$ is the maximum power reduction of unit *i* in a single period.

Unit minimum shutdown time constraints:

$$P_{ev,t}^{s}\leq P_{ev,t}^{\max}$$

In the equation: $P_{ev,t}^{\max}$ is the maximum power rechargeable during the *t* period;

$$\sum_{t=1}^{T}P_{ev,t}^{s}=P_{ev,t}^{sum}$$

In the equation: $P_{ev,t}^{sum}$ is the sum of all electric vehicles charged in a day;

Abandon wind, abandon light restraint:

$$0 \le \Delta P^{s}_{wind,m,t} \le P^{s}_{wind,m,t}$$
$$0 \le \Delta P^{s}_{pv,n,t} \le P^{s}_{pv,n,t}$$

In the equation: $\Delta P^{s}_{wind,m,t}$ is the abandoned wind power; $P^{s}_{wind,m,t}$ is the predicted wind power; $\Delta P^{s}_{pv,n,t}$ is the power of abandoned light; $P^{s}_{pv,n,t}$ is the predicted photovoltaic output.

2.2. Optimal scheduling modeling at spatial scale

The optimization strategy on the time scale determines the unit output, scenery output and the total charging load curve of electric vehicles in the transmission network layer, and the distribution network side needs to optimally distribute the total charging load of electric vehicles to each node in the distribution network according to the power supply situation of the transmission network and the spatial location distribution of electric vehicles in the distribution network. Therefore, this paper proposes a spatial optimization scheduling strategy based on the optimal power flow in the distribution network. By optimizing the power flow distribution, the total charging load of electric vehicles is optimally allocated to each node of the distribution network, and the optimization variable is the charging load of electric vehicles at each node in each period.

2.2.1. Objective function

Generally, the distribution network operator hopes to distribute the charging load of electric vehicles on the most suitable nodes to improve the power flow distribution of the distribution network and reduce the total network loss of the distribution network. Therefore, the optimal scheduling model on the spatial scale aims to reduce the total network loss of the distribution network, and optimally distributes the EV charging load on the nodes of the distribution network. The objective function of optimal scheduling policy can be expressed as:

$$f = \min \sum_{t=1}^{T} P^{s}_{\mathrm{Loss},t}$$

In the equation: $P^{s}_{\mathrm{Loss},t}$ represents the total distribution network active power loss considered at time t

(2) Constraint conditions

Node power balance constraints:

$$P^{s}_{G\alpha,t} - P_{D\alpha,t} - P^{s}_{ev,\alpha,t} - P^{s}_{T\alpha,t} = 0$$

$$Q^{s}_{G\alpha,t} - Q_{D\alpha,t} - Q^{s}_{T\alpha,t} = 0$$

In the equation: $P^{s}_{G\alpha,t}$ is the active power emitted by the active power supply of node α under scene s at time period t; $P_{D\alpha,t}$ is the active load of node α in time period t; $P^{s}_{ev,\alpha,t}$ is the electric vehicle load charged at node α in time period t under scenario s; $P^{s}_{T\alpha,t}$ is the active power transmitted by node α at time period t under scene s; $Q^{s}_{G\alpha,t}$ is the reactive power emitted by the reactive power supply of node α in scene s at time period t; $Q_{D\alpha,t}$ is the reactive load of node α in time period t; $Q^{s}_{T\alpha,t}$ is the reactive power transmitted by node α at time period t under scene s; K is the set of nodes except the equilibrium node in the distribution network.

Node voltage amplitude constraints:

$$V_{\alpha,\min} \le V^{s}_{\alpha,t} \le V_{\alpha,\max}$$

In the equation: A and B are the maximum and minimum allowable voltage values of node α respectively.

Node transmission power constraints:

$$\left|P_{\alpha j,t}^{s}\right| \leq P_{\alpha j,\max}$$

In the equation: $P_{ev,\alpha}^{\max}$ is the maximum power that can be transmitted by the line between node α and node j; K 'is the set of all nodes in the distribution network. $P_{\alpha j,t}$ is the active power transmitted by the line between node α and node j at time period t in scenario s.

Charging power constraints:

$$0 \leq P_{ev,\alpha,t}^{s} \leq P_{ev,\alpha}^{\max}$$

In the equation: $P_{ev,\alpha}^{\max}$ is the maximum rechargeable power of node α.

Constraints on upper-layer scheduling results:

$$\sum_{\alpha \in I} P_{ev,\alpha,t}^{s} = P_{ev,t}^{s}$$

In the equation: $P_{ev,t}^{s}$ is the charging load at time t after time scale optimization; I represents a collection of nodes containing charging stations.

2.3. Solution method

2.3.1. Transmission side objective function solving method

In this paper, in the simulation analysis of a large number of electric vehicles connected to the grid, the electric vehicle load is regarded as a dispatchable load, and the collaborative optimization of the power generation side and the load side is considered as a whole, so as to achieve the multi-objective optimization of the power generation and operation cost on the transmission side, improve the absorption rate of new energy landscape, and reduce the charging cost of the owner. The optimal scheduling time span takes 24 hours as a cycle, comprehensively analyzes the power output state of thermal power units, the absorption rate of new energy scenery and the EV charging situation, and reduces the cost expenditure and the fluctuation of the grid load on the basis of ensuring the changing needs of the owners. According to the above modeling and analysis, the piecewise linearization method is used to process the upper nonlinear model data, and then the Gurobi solver is used to solve the optimal solution of the above model.

2.3.2. Distribution side objective function solving method

The quadratic flow constraint is considered in the spatial model constructed in this paper, because it is not easy to obtain the global optimal solution when solving the optimal value by the algorithm, and it often stops when solving the local optimal. In this paper, the second order cone relaxation method is used to convex relax the constructed constraints, and the second order cone programming method is used to solve the above targets, which can ensure the accuracy of the target solution and improve the efficiency of the solution.

3. Analysis of numerical examples

In order to verify the feasibility and effectiveness of the proposed EV charging scheduling strategy considering the spatiotemporal optimization of new energy into the grid, this section constructs a power system simulation model including thermal power units, wind farms, photovoltaic arrays, transmission networks, distribution networks and charging stations, as shown in Figure 1.

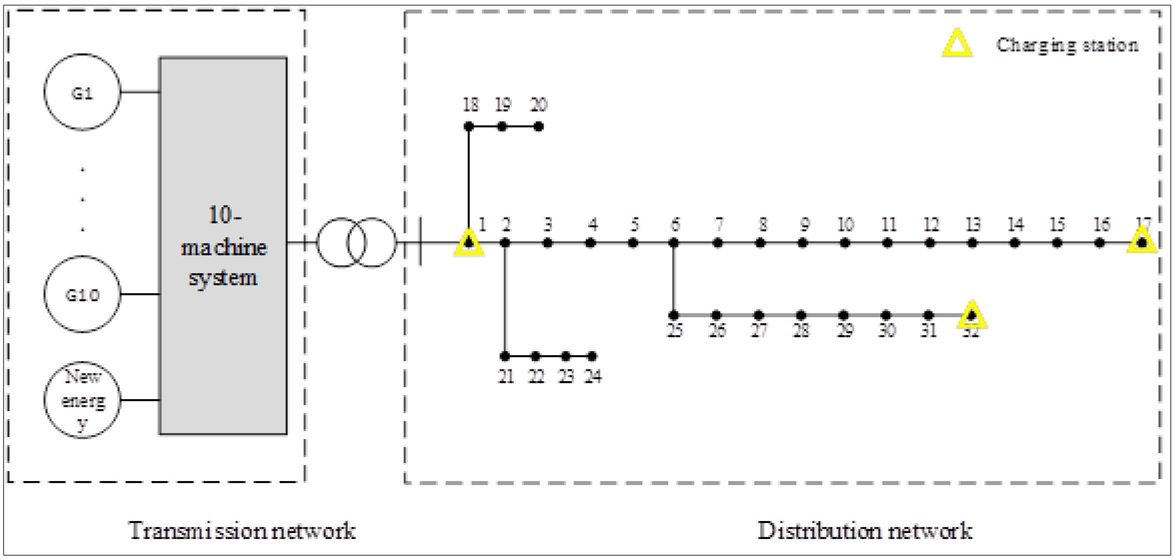

Figure 1 Simulation model of Power system

3.1. Analysis of optimization results on time scale

In order to facilitate calculation, the model in this paper only considers the large-scale solar new energy access in the upper layer, and the small-scale solar new energy access in the lower distribution network layer is temporarily ignored. Considering the above situation, the following calculation example is set for analysis:

Example 1: Electric vehicles are not included in the grid.

Example 2: Including electric vehicles, unordered charging, the electricity price is the constant electricity price in Figure 2.

Example 3: Including electric vehicles, optimal scheduling, constant electricity price.

Example 4: Including electric vehicles, optimized scheduling, peak-valley electricity price, and charging electricity price as shown in Figure 2

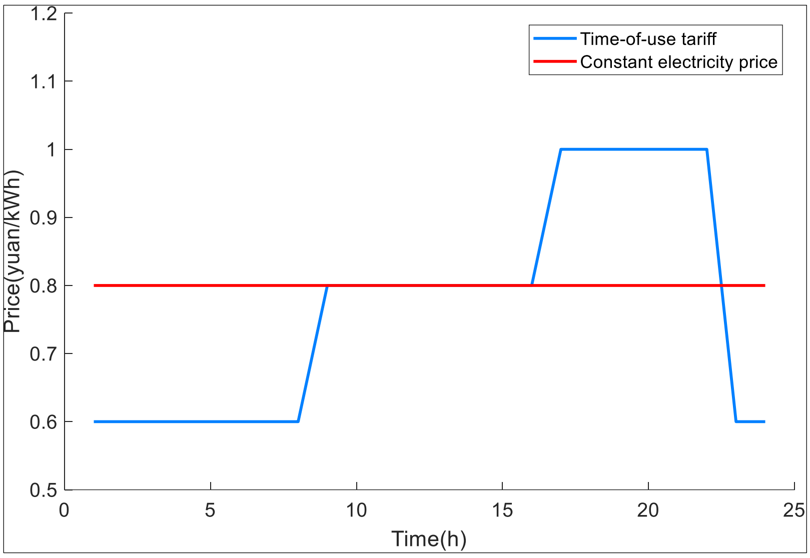

Figure 2 Price of charging

In the optimization model of the transmission network side, the cost pairs of each example are shown in Table 1. The comparison results of fuel cost of four examples show that when the disordered charging electric vehicle is added to example 2, the system operation cost reaches 527306.159 yuan, which is the highest among the four examples. By comparing the fuel cost of example 1 and example 2 in Table 1, we can see that, The fuel cost in example 2 is 93,367 yuan higher than that in example 1, because a large number of electric vehicles are connected to charge, which is equivalent to an electrical load, increasing the power demand on the load side, making the thermal power unit need to increase the power output, and thus the cost rises. By comparing the unit start-up cost in example 1 and example 2, it can be seen that the start-up cost in example 2 is 2,400 yuan higher than that in example 1, indicating that due to the disorderly access of electric vehicles, the start-up plan of the original unit has changed and the start-up cost of the thermal power unit has increased. The comparison of the results of example 2 and example 3 shows that the electric vehicle optimization scheduling method proposed in this paper can reduce the fuel cost of the system and the start-up cost of the thermal power unit, and optimize the operating cost of the system. This is because the model proposed in this paper improves the start-up plan of the thermal power unit and reduces the maximum output cost of the thermal power unit by optimizing the charging plan of the user. By comparing the results of example 3 and example 4, under the guidance of TOU price, example 4 can reduce the charging cost of EV users, while the fuel cost and start-up cost of the system hardly change. Further combined with Figure 3 and Figure 4, it can be seen that under TOU price, the dispatchable charging load of EV is transferred to the moment when the charging price is lower.

Table 1 Results of different examples

Example	System operating cost（yuan）	Fuel cost (yuan)	PM2.5 emission cost（yuan）	Start-up cost （yuan）	Charging cost （yuan）	Abandonment cost（yuan）
Example 1	425332.4853	409996.2344	12746.2509	2590	0	0
Example 2	527306.159	503363.3577	15547.202	4990	3405.6	0
Example 3	521555.3052	498206.9435	15472.7617	4470	3405.6	0
Example 4	521654.2765	498220.53	15489.794	4470	3473.95	0

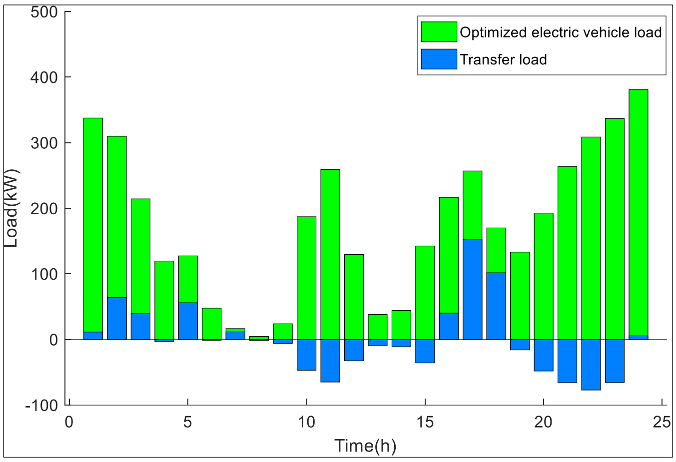

Figure 3 Result of example 3

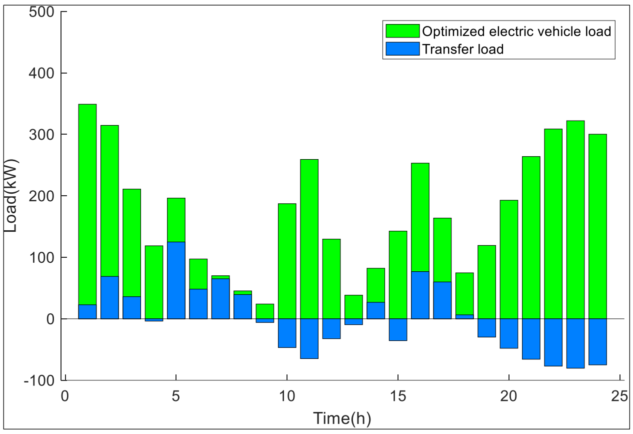

Figure 4 Result of example 4

3.2. Analysis of optimization results on spatial scale

Distribution network side model solution is based on the model simulation calculation of IEEE33 nodes. In terms of electric vehicles, this paper mainly considers that three charging stations are connected to the distribution network, and studies the optimal spatial distribution of electric vehicles charging at the distribution network layer according to the optimal scheduling scheme of electric vehicles obtained at the transmission network side. The basic capacity of this distribution network is set to 100MVA, the reference voltage is set to 12.66kV, and the maximum output of electric vehicles in this distribution network model is set to about 450kW.

The following three examples are set for comparative analysis

- Example 5: Without electric vehicles.
- Example 6: Including electric vehicles.
- Example 7: Based on example 4, the charging load of different nodes is optimized.

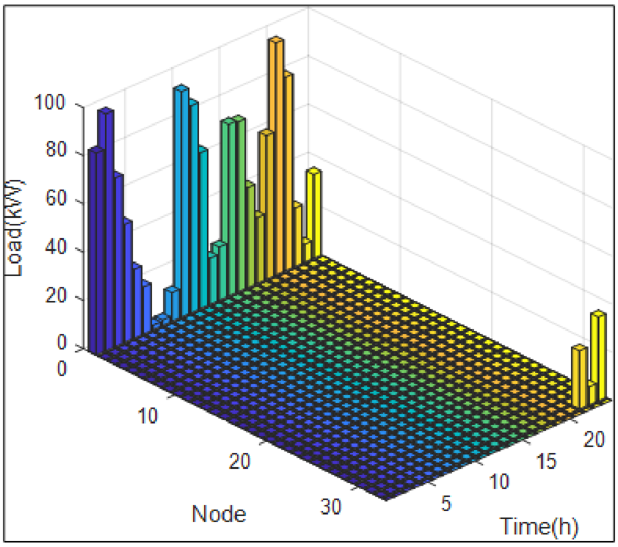

Figure 5 Load per node of increasing

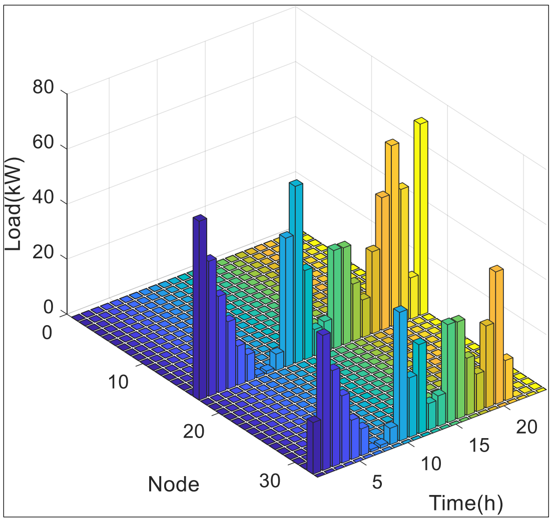

Figure 6 Load per node of decreasing

According to the transfer distribution diagram of dispatchable load of electric vehicles at the lower level in FIG. 5 and FIG. 6, according to the optimal EV charging scheduling strategy obtained by the upper level model and the power supply situation at the transmission side, the dispatchable charging load of electric vehicles at the distribution network side in example 6 is mainly transferred to the charging station at node 1. The load of electric vehicles at the charging stations at nodes 17 and 32 is almost reduced at every moment. From the distribution model of the three charging stations in the distribution network in this paper, it can be seen that charging station 1 is connected to node 1, and node 1 is closest to the first end of the distribution network, indicating that charging electric vehicles concentrated near the first end of the distribution network can reduce the total network loss of the distribution network and improve the operation economy of the distribution network. The total network loss under each calculation example is shown in Table 2.

Table 2 Total network loss of Examples

Example	Example 5	Example 6	Example 7
Total network loss (MW)	0.25795	0.34550	0.32590

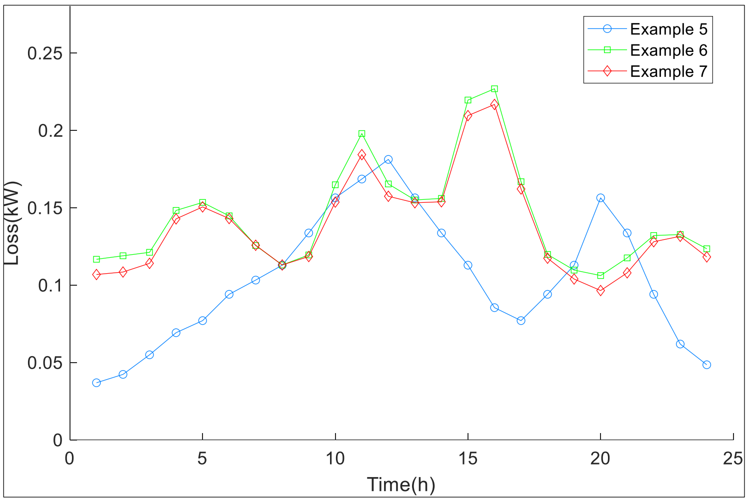

Figure 7 Curve of loss

It can be seen from Figure 7 and Table 2 that by taking the upper optimal scheduling strategy and regional division according to the lower optimization model proposed in this paper, the total network loss of the distribution network increases from 2.5795kW to 3.445kW due to disorderly charging of electric vehicles by comparison of example 5 and example 6. By comparison of example 6 and example 7, it can be seen that the total network loss of the distribution network decreases from 3.445kW to 3.2590 kW after adopting the optimization method proposed in this paper. This is because in the calculation example set in this paper, two of the three charging stations are far away from the first end of the distribution network, and the proportion of charging load far away from the first end of the distribution network is larger. According to the radiation structure of the distribution network, the power is transmitted from the relaxed node to the node with a longer distance, and the loss should be greater. After optimized scheduling, the dispatchable charging load of electric vehicles is transferred to the charging station at node 1, thus reducing the total network loss of the distribution network. At the same time, in example 6, when electric vehicles are connected to the power grid in a disorderly manner, the system network loss is the largest, reaching 3.445kW, indicating that orderly dispatch management of electric vehicles is not carried out, resulting in the greatest impact on the power grid. On the one hand, the above analysis proves the rationality of the optimal scheduling strategy of the upper layer; on the other hand, it also gives suggestions, that is, the construction of charging piles should consider the regional attributes, and more charging facilities for electric power vehicles can be set near the slack bus, so as to better reduce the total network loss of the system.

4. Conclusion

In order to enable EV to coordinate with power supply, this paper proposes an EV charging scheduling strategy based on spatio-temporal optimization model, which can coordinate and optimize EV charging from time and space respectively. Through the analysis of numerical examples, the following conclusions can be drawn:

First of all, from the perspective of demand response mechanism, the fixed electricity price mode is difficult to effectively regulate the charging behavior of EV users, while the peaking and valley electricity price mechanism based on load fluctuations can significantly guide users to charge during load off-peak periods, which verifies the key role of price signals in demand-side management. Secondly, at the level of distribution network operation optimization, the research results show that: by preferentially distributing the charging load to the nodes near the first end of the distribution network, while concentrating the discharge load on the end nodes of the distribution network, the network loss can be significantly reduced and the system operation economy can be improved. This spatial optimization strategy not only considers the power flow characteristics, but also fully reflects the influence of distribution network topology on energy transmission efficiency.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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