Optimal Load Scheduling in Coupled Power and Transportation Networks

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***Abstract*—As a part of the global decarbonization agenda, the electrification of the transport sector involving the large-scale integration of electric vehicles (EV) constitues one of the key initiatives. However, the introduction of EV loads results in more variable electrical demand profiles and higher demand peaks, challenging power system balancing, voltage and network congestion management. In this paper, a novel optimal load scheduling approach for a coupled power and transportation network is proposed. It employs an EV charging demand forecasting model to generate the temporal-spatial distribution of the aggregate EV loads taking into account the uncertainties stemmed from the traffic condition. An AC optimal power flow (ACOPF) problem is formulated and solved to determine the scheduling decisions for the EVs, energy storage units as well as other types of flexible loads, taking into account their operational characteristics. Convex relaxation is performed to convert the original non-convex ACOPF problem to a second order conic program. Case studies demonstrate the effectiveness of the proposed scheduling strategy in accurately forecasting the EV load distribution as well as effectively alleviating the voltage deviation and network congestion in the distribution network through optimal load scheduling control decisions.**

***Index Terms*—Electric vehicle, load scheduling, network congestion management, power and transportation networks.**

NOMENCLATURE

$t \in \{1, \dots, T\}$	Index and set of time periods
$e \in \{1, \dots, E\}$	Index and set of electric vehicles
$i \in \{1, \dots, I\}$	Index and set of traffic nodes
$x \in \{1, \dots, X\}$	Index and set of coupled nodes
D_{ij}	Distance between traffic node i and j
L_e^{dep}, L_e^{arr}	Departing and arriving positions of EV e
t^{dep}, t^{arr}	Departing and arriving times of EV
$B_{e,t}$	State of charge (SoC) of EV e at time t
B_e^{set}	Threshold SoC for charging of EV e
B_e^{req}	Required SoC for fulfilling the next day's travel plan of EV e
$f_{e,i,t}$, $s_{e,i,t}$	Fast and slow charging status of EV e at node i at time t
$P_{i,t}^{tot}$	Aggregate charging power of node i at time t
$DRP_{x,t}$	Total demand response potential of flexible loads at coupled node x at time t
$DR_{x,t}$	Total demand response of node x at time t
$P_{x,t}^L, Q_{x,t}^L$	Total active/reactive power at node x at time t after demand response
P_x, P_x^G, P_x^L	real injected/generated/load power at node x
Q_x, Q_x^G, Q_x^L	reactive injected/generated/load power at node x
U_x, δ_x	voltage and voltage angle at node x
$G_{x,y}, B_{x,y}$	conductance and susceptance between node x and node y
$P_{x,t}^0$	Total inflexible demand of node x at time t
$\underline{U}, \overline{U}$	Minimum and maximum voltage limit
$U_{x,t}$	Voltage of node x at time t
$S_{x,t}^{sen}, S_{x,t}^{rec}$	Apparent power flow leaving the reference sending node and reaching the reference receiving node x at time t
$\overline{S}_{xx'}$	Thermal capacity of line (x, x')

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I. INTRODUCTION

Environment and energy security concerns have paved the way for the extensive decarbonization of energy systems through large-scale integration of renewable generation and electrification of transport and heat sectors, both in China and beyond [1]. However, this paradigm shift introduces significant challenges to the operation and development of future power systems. At the generation side, the high variability and intermittency of renewable generation challenges the system balancing. At the demand side, the electrification of transport and heat sectors not only intensifies the overall electrical energy consumption, but disproportionately increase the peaks of overall demand (due to the temporal patterns of users' driving and heating requirement), which may overload the distribution network, create voltage deviation and network congestion [2], [3]. The increase of EV in transportation network also aggravates the traffic congestion and charging congestion, namely high charging queueing time [4]. Therefore, suitably managing the EV charging loads constitutes an imperative step in secure and economic operation of power and transportation systems.

The charging options of EV generally include fast and slow charging. The former involves charging the EV at a charging station or a charging pile which entails higher range anxiety and thus higher charging power. This option is primarily linked to the travel plan or the commuting behavior of EV users and thus the spatial distribution of EV charging loads. In this context, charging navigation optimization approaches are generally employed to manage the fast charging loads in the presence of the variability and uncertainty stemmed from the traffic conditions. A stochastic dynamic pricing and EV charging service management method is proposed in [5] to provide optimal charging navigation decisions for EV users when their battery need to be recharged. Authors in [6] investigate the impact of traffic information on the driving and charging behaviors of EV users using historical data. Authors in [7] proposed a charging navigation model incorporating real-time perception of traffic information and crowd sensing techniques. Although these previous works take the impact of traffic condition on EV behaviors into account in determining the spatial distribution of charging loads, the temporal flexibility of EV loads (i.e. the ability of EV loads to shift in time) is neglected.

Slow charging involves charging the EV at home or workplace while parking for a more significant amount of time. This option is linked to the temporal load distribution of EV. In this context, previous research focus lies in DR management programs for EV fleets or EV aggregators. An uncertainty mitigating model is proposed in [8] to optimize the EV charging time, making uncertainty from different periods compensate for each other and make use of the temporal flexibility of EV aggregators. In [9], parking lots with charging facilities are modeled as load aggregators which optimize the charging and discharging behaviors of an EV fleet. Workplace charging of EV enabled by on-roof photovoltaic (PV) panels of smart buildings is studied in [10], where the Vehicle-to-Grid (V2G) capability of EV to inject stored energy back to the grid is also taken into account. Similar optimization approaches are employed in [11], [12] which examine PV-assisted commercial buildings for EV charging. Although these previous works contribute to the optimal temporal management of EV charging loads in the power network, the influence of traffic condition on the EV navigation and subsequently its charging behaviors is neglected.

In order to address the limitations of previous works, this paper proposes a novel load scheduling approach from the power network operator's perspective. More specifically, the interaction between the EVs and the coupled power and transportation networks is analyzed, and a load forecasting model is developed to accurately forecast the spatial-temporal distribution of the EV charging loads. Given this initial EV load distribution, an AC optimal power flow (ACOPF) problem is proposed to optimize the scheduling decisions for EVs, energy storage units as well as other types of flexible loads, taking into account their operating characteristics. Unlike [13], [14] which solve ACOPF in its non-convex form using nonlinear programming solvers, convex relaxation [15] is performed, and the ACOPF problem is transformed to a second order conic program (SOCP), which can be solved more efficiently for an optimal solution. Case studies based on a real-world system involving a coupled power and transportation networks in Nanjing, China demonstrate the effectiveness of the proposed load scheduling method in effectively alleviating the voltage deviation and network congestion for the power network, as well as mitigating the charging queueing time for the transportation network.

The rest of this paper is organized as follows. Section II outlines the proposed traffic-information-informed EV demand forecasting model. Section III details the proposed load scheduling optimization model. Section IV presents the case studies and illustrative results demonstrating the value of the propose method. Finally, Section V concludes.

II. Traffic-Information-Informed EV Charging Demand Forecasting Model

A. Interaction Between power and transportation Networks

The interaction between the transportation network, the power grid, and the EV charging loads is shown in Fig. 1.

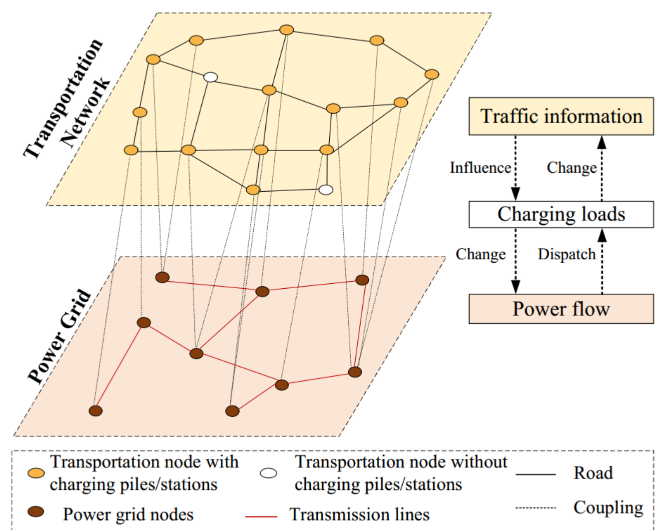

Fig. 1. Interaction between transportation network, power grid and charging loads of electric vehicles.

In the coupled power and transportation networks, the driving velocity and path selection of each EV is influenced by the traffic information, e.g. the traffic flow, the road grade, road facilities, etc. In addition, the total driving and charging queuing time also affect the charging decisions of the EV users, namely the selection of charging time and location, which is related to the spatial-temporal distribution of the charging loads. From the grid operator's perspective, the traffic information should be available to accurately forecast the initial charging load distribution and coordinate the load scheduling.

Meanwhile, after the power grid operator dispatches the charging loads, the travelling and charging decision of EVs especially those with fast charging demand, will conversely result in the change of the traffic condition.

B. Charging Forecasting Model of Single Electric Vehicle

Denoting the distance matrix for the traffic network as $D = (D_{i,j}) \in \mathbb{R}^{I\times I}$, where i and j are the connecting nodes of a road. When $D_{i,j} = 0$ the two nodes overlap. Infinite $D_{i,j}$ means that the two nodes are unconnected.

The departing time t_e^{dep}, departing L_e^{dep} and the arriving L_e^{arr} positions of the EVs are determined via Monte Carlo simulation. Assuming that EV chooses the shortest path between L_e^{dep} and L_e^{arr} as commuting path, which is found by the Dijkstra algorithm. Assuming the shortest path passes in total of K nodes from the departing node to arriving node.

Denoting the average driving velocity (km/h) between node i and j as $v_{i,j}$, it reflects the uncertainty of traffic information in the traffic network, and is affected by various factors such as road grade, time, and traffic flow. The velocity model is shown as (1)-(2).

$$v_{i,j} = \alpha_1 v_0/[1 + (C_{i,j}/\overline{C}_{i,j})^{\beta}] \tag{1}$$

$$\beta = \alpha_2 + \alpha_3(C_{i,j}/\overline{C}_{i,j})^3 \tag{2}$$

where α_1, α_2, α_3, and β are regression and correction coefficients, varying with the road grade. v_0 is the maximum velocity allowed on each road. $C_{i,j}$ and $\overline{C}_{i,j}$ denotes the traffic flow (which is generated via Monte Carlo simulation) and the capacity of road (i, j), respectively.

The state of charge (SoC) of EV e at t can be written as:

$$B_{e,t} = \eta(B_{e,t-1} - \Delta l \Delta B) \tag{3}$$

where Δl denotes the driving distance from $t-1$ and t, ΔB represents the energy consumption per km. η is the efficiency parameter, indicating the energy loss caused by starting and braking operations [16]. When the remaining SoC is not enough to complete the travel plan (i.e. raising range anxiety), the EV is assumed to charge at the nearest charging station.

Therefore, the arriving time of EV can be calculated as:

$$t^{arr} = \begin{cases} t^{dep} & \text{if } d = 1 \\ t^{dep} + \sum_{d=2}^{K}(D_{d-1,d}/v_{d-1,d} + t^{chr} + t^{wt}) & \text{if } d \neq 1 \end{cases} \tag{4}$$

where $D_{d-1,d}$ and $v_{d-1,d}$ represent the distance and the average driving velocity between node $d-1$ and d. t^{chr} and t^{wt} represent the charging time and the waiting time, respectively. Notably, when the EVs have enough SoC, both t^{chr} and t^{wt} are set to zero.

C. Aggregate Charging Forecasting Model

In this paper, EVs are divided into three categories, namely private car, taxi, and bus. Different categories of vehicles exhibit distinct driving and charging behaviors. Private cars typically commute between the user's home and work place, and their predefined fast/slow charging power is 120/7 kW. Electric taxis have irregular travelling behaviors whose charging power is similar to that of the private cars. Electric buses shuttle regularly and their predefined fast/slow charging power is 400/200 kW. The charging status model of the private cars can be expressed as:

$$\begin{cases} s_{e,i,t}^1 = 1, & \text{if } B_{e,t} < B_e^{set}, i = L_e^{dep} \\ f_{e,i,t}^1 = 1, & \text{if } B_{e,t} < B_e^{set}, i \neq L_e^{dep} \\ f_{e,i,t}^1 = s_{e,i,t}^1 = 0, & \text{if } B_{e,t} \geq B_e^{set} \end{cases} \tag{5}$$

where $f_{e,i,t}^1$ and $s_{e,i,t}^1$ represent the fats/slow charging status of private car e is at node i and t; B_e^{set} is the minimum level of SoC to travel from the current position to the destination, namely it denotes the threshold SoC for charging.

Similarly, the charging status models of electric taxis and buses can be derived following the same logic of (5). Based on the derived charging status models which represent the spatial and temporal distribution of the charging power of each EV, the forecasted aggregate charging demand of the EV population can be expressed as:

$$\begin{aligned} P_{i,t}^{tot} &= \sum\nolimits_{e=1}^{E_1}[P_f^p f_{e,i,t}^1 + P_s^p s_{e,i,t}^1] + \\ \sum\nolimits_{e=1}^{E_2}&[P_f^p f_{e,i,t}^2 + P_s^p s_{e,i,t}^2] + \sum\nolimits_{e=1}^{E_3}[P_f^b f_{e,i,t}^3 + P_s^b s_{e,i,t}^3] \end{aligned} \tag{6}$$

where E_1, E_2, E_3 represents the total number of EVs in each category, P_f^p and P_s^p denote the fast and slow charging power of electric private cars and taxis, respectively. P_f^b and P_s^b denote the fast and slow charging power of electric buses, respectively. $P_{i,t}^{tot}$ represents the total EV charging loads at node i and time t before introducing any demand response actions (as optimized in Section III).

III. Optimal Load Scheduling Optimization Model

A. Scheduling Potential of Flexible Loads

Traffic nodes with charging piles or stations are physically connected to some nodes of the power network, and this subset of traffic nodes is referred to as the coupled nodes hereafter. Notably, more than one traffic nodes can couple with one node of the power network. In this paper, we assume that the set of coupled nodes coincides the set of nodes of the power network.

In this section, a load scheduling model is proposed to optimize the shedding and temporal shifting decisions of EV, air conditioner (AC) and water heater (WH) charging loads, as well as the charging/discharging decisions of energy storage (ES) units, targeted to minimize the average voltage deviation in the power network. Each coupled node has a dispatching operator to implement the optimal scheduling decisions.

The demand response potential (DRP) model of an EV can be expressed as:

$$DRP_{e,x,t} = \begin{cases} 0 & \text{if } B_{e,x,t} + P_e(t_{e,x}^{dep} - t) < B_e^{req} \\ P_e, & \text{if } B_{e,x,t} + P_e(t_{e,x}^{dep} - t) \geq B_e^{req} \end{cases} \tag{7}$$

If the participation in the demand response program of EV e at t results in low SoC level which cannot fulfill the user's travel plan for the next day, the DRP is equal to 0; otherwise, the DRP is equal to the rated charging power of EV P_e which is dependent to the category and charging status of EV e.

The DRP model of an AC can be expressed as:

$$DRP_{a,x,t} = \begin{cases} P_a, & \text{if } TP_{a,x,t} \leq TP_{a,x}^{set} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where P_a, $TP_{a,x}^{set}$, and $TP_{a,x,t}$ denote the rated power of AC, the target and the operational temperatures, respectively.

The DRP model of an WH can be expressed as:

$$DRP_{w,x,t} = \begin{cases} P_w, & \text{if } TP_{w,x,t} \geq TP_{w,x}^{set} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

where P_w, $TP^{set}_{w,x}$, and $TP_{w,x,t}$ denote the rated power of WH, the target and operational temperatures, respectively.

$$E_t = (1-\tau)E_{t-1} + \eta_c^{es} P^c_{es,x,t}\Delta t - P^d_{es,x,t}\Delta t/\eta_d^{es} \tag{10}$$

where Δt is the temporal resolution, E_t denotes the energy in the ES unit at time t. τ is the degradation coefficient. $P^c_{es,x,t}$ and $P^d_{es,x,t}$ are the charging and discharging power of ES unit at t, respectively. η_c^{es} and η_d^{es} are the charging and discharging energy efficiency coefficient of ES unit at t, respectively.

The aggregate DRP for node x at t can be expressed as:

$$\begin{aligned} DRP_{x,t} = \sum\nolimits_a DRP_{a,x,t} + \sum\nolimits_w DRP_{w,x,t} + \\ \sum\nolimits_e DRP_{e,x,t} + \sum\nolimits_{es} [P^c_{x,es}(t) - P^d_{x,es}(t)] \end{aligned} \tag{11}$$

B. Optimal Scheduling Based on SOCP

Based on the above DRP models, the proposed scheduling model can be formulated as follows.

$$\min_{DR_{x,t}, P^G, Q^G, U_x, \delta_x} C^p(P^G) + C^q(Q^G) \tag{12}$$

$$DR_{x,t} \leq DRP_{x,t} \tag{13}$$

$$\begin{aligned} P_x = P_x^G - P_x^L = U_x \sum_y^X (U_y(G_{x,y} cos(\delta_x - \delta_y) \\ + B_{x,y} sin(\delta_x - \delta_y))) \end{aligned} \tag{14}$$

$$\begin{aligned} Q_x = Q_x^G - Q_x^L = U_x \sum_y^X (U_y(G_{x,y} sin(\delta_x - \delta_y) \\ - B_{x,y} cos(\delta_x - \delta_y))) \end{aligned} \tag{15}$$

$$P^L_{x,t} = P^0_{x,t} + P^{tot}_{x,t} - DR_{x,t} \tag{16}$$

$$\underline{U} \leq U_{x,t} \leq \overline{U} \tag{17}$$

$$S^{sen}_{x,t} \leq \overline{S}_{xx'} \tag{18}$$

$$S^{rec}_{x,t} \leq \overline{S}_{xx'} \tag{19}$$

where $C^p()$ and $C^q()$ denote the active and reactive power cost, respectively. Constraint (13) restricts that the actual demand response is less or equal to the DRP. Constraints (14-16) express the nodal active and reactive power balance of the power network. Constraints (17-19) express the voltage and thermal limits of the power network.

The origianl formulation of the ACOPF problem is non-convex and NP-hard, to pursue non-convexity and foster higher computational efficiency, the SOCP convex relaxation technique to employed. Convex relaxations increase the feasible space to include the non-convex feasible space.

SOCP relaxation of the power flow equations involves the introduction of new variables representing the product of voltages. Given voltage at node x is represented in rectangular coordinates as $U_x = U_{dx} + jU_{qx}, \forall x \in N_X$, the squared voltage magnitude is represented by c_{xx}. New variables c_{xy} and s_{xy} are introduced to represent the real and imaginary parts of the product of voltages at node x and its conjugate at node y respectively, $\forall x, y \in N_X$. Using these new variables, the power flow equations (14-15) are changed as (20-21).

$$P_x^G - P_x^L = c_{xx}G_{x,x} + \sum_{y \neq x}^X (c_{xy}G_{x,y} - s_{xy}B_{x,y}) \tag{20}$$

$$Q_x^G - Q_x^L = -c_{xx}B_{x,x} + \sum_{y \neq x}^X (-c_{xy}B_{x,y} - s_{xy}G_{x,y}) \tag{21}$$

However, the following equality constraints need to be added to the optimization problem,

$$c_{xy} = c_{yx}, s_{xy} = -s_{yx}, \forall \{x, y\} \in N_L \tag{22}$$

$${c_{xy}}^2 + {s_{xy}}^2 = c_{xx}c_{yy}, \forall \{x, y\} \in N_L \tag{23}$$

where N_L is the set of lines in the power grid considered. The addition of the equality constraint (23) makes the new representation of the power flow equations non-convex. By changing the equality constraint to an inequality as illustrated in (24), the power flow equations are a form of SOCP and are now convex.

$${c_{xy}}^2 + {s_{xy}}^2 \leq c_{xx}c_{yy}, \forall \{x, y\} \in N_L \tag{24}$$

Hence, replacing (14-15) with (20-22), the problem is reformed as (25).

$$\begin{aligned} \min_{DR_{x,t}, P^G, Q^G, U_x, \delta_x} C^p(P^G) + C^q(Q^G) \\ \text{s.t.}(13), (16-19), (20-22), \text{and}(24) \end{aligned} \tag{25}$$

IV. Case Studies

The transportation network is simplified from three areas of Nanjing. The 110kV power grid is built from the real-world data provided by the State Grid, Nanjing corporation. The historical EV charging data comes from open access data in "Telaidian" APP. The number of three types of EVs in the simulation are 1600, 100, and 70, respectively. The initial forecasted charging loads are shown as Fig. 2. It can be observed that the aggregate charging loads reaches the peak from 18:00 p.m. to 3:00 a.m. the next day. The forecasted loads of three types of EV are shown as Fig. 3.

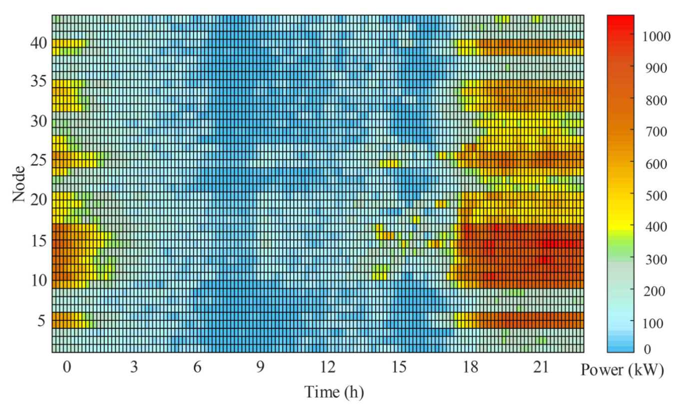

Fig. 2. Forecasted charging loads of electric vehicles.

The profile of aggregate loads before and after scheduling is shown as Fig. 4. The scheduling redistributes the aggregate flexible loads. However, the uncontrolled charging loads heavily overlap with other flexible loads such as AC and WH, leading to severe voltage deviation and network congestion in the power grid, as is shown in Fig.5. The integration of

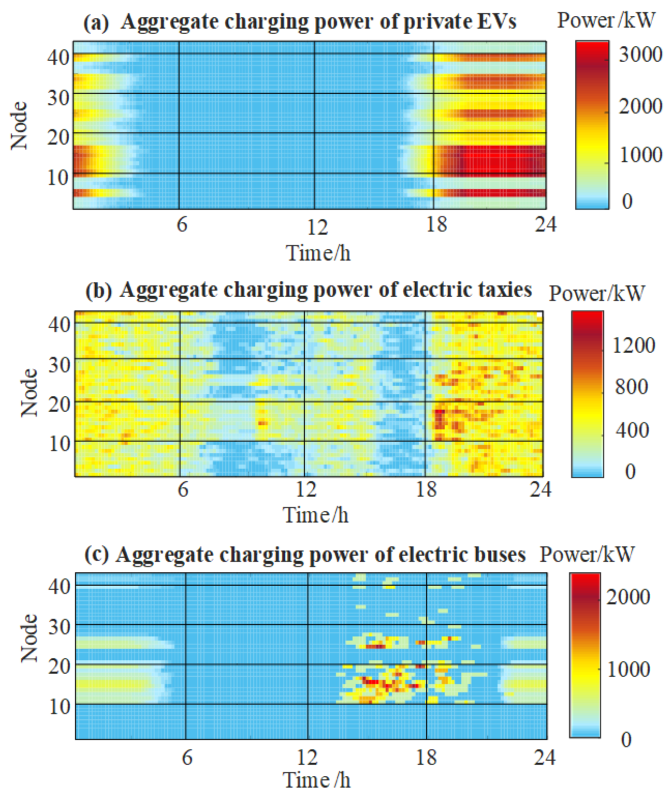

Fig. 3. Forecasted loads of three types of EV.

EV aggravates the voltage deviation, and the voltage deviation reaches the valley at about 20:00, which is consistent with the time when the charging load power reaches the peak.

The voltage profile of each node after scheduling is shown as Fig. 6. The network congestion before and after scheduling are shown as Fig. 7 and Fig. 8, respectively. It can be seen that the proposed scheduling method can alleviate voltage deviation and network congestion, especially for nodes and transmission lines with unstable operational state.

The influence of the load scheduling on the transportation network is also analyzed. The hourly average charging queueing time before and after dispatching is shown as Fig. 9. The result demonstrates the effectiveness of the load scheduling in reducing charging queueing time.

V. Conclusion

Optimal load scheduling in coupled power and transportation networks plays a vital role towards the secure and economic operation of power and transportation systems. This paper proposes a traffic-information-informed EV charging demand forecasting model to accurately forecast the initial spatial-temporal distribution of EV charging loads. Further, a load scheduling optimization model is proposed to determine the optimal shedding and temporal shifting of EV charging loads based on the initial distribution of EV loads, as well as scheduling the operation of energy storage units and other types of flexible loads, targeted to minimize the average voltage deviation of the power network. Case studies are carried out on a real-world system involving a coupled power and transportation networks in Nanjing validate the effectiveness of the proposed method in alleviating the voltage deviation and network congestion for the power network as well as reducing

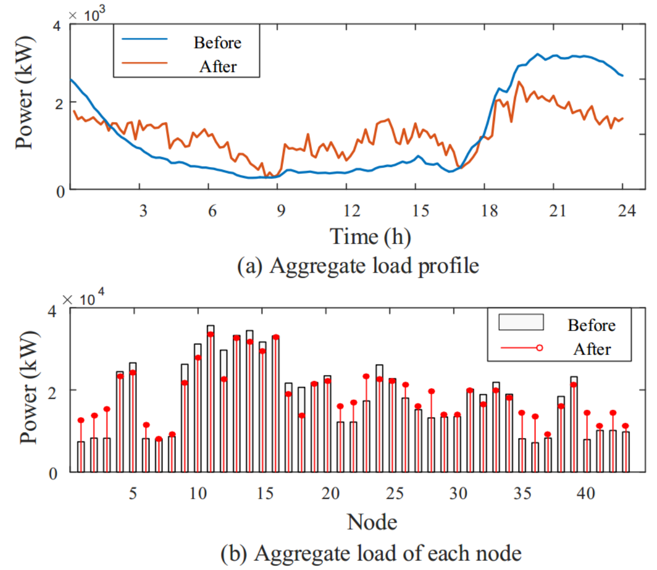

Fig. 4. Profile of aggregate loads before and after scheduling.

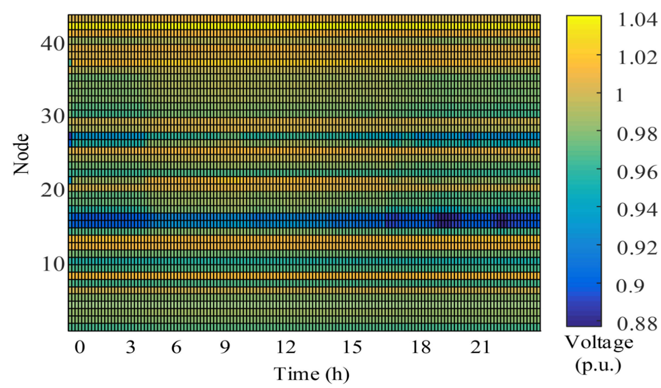

Fig. 5. Voltage profile before scheduling.

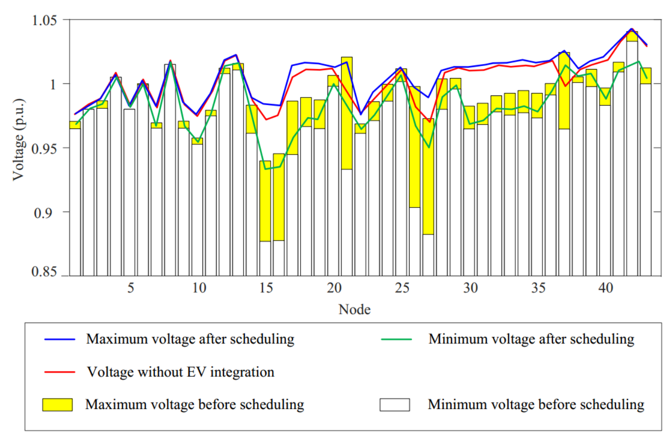

Fig. 6. Voltage profile after scheduling.

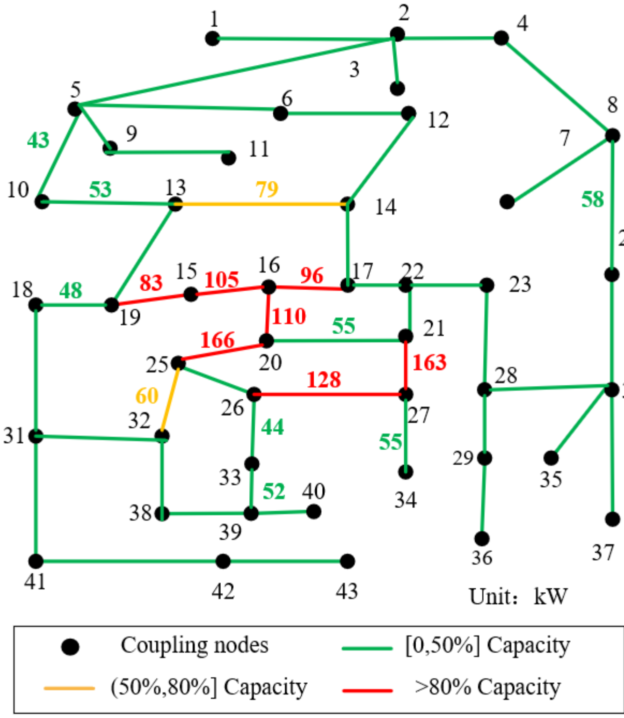

Fig. 7. Network congestion before scheduling.

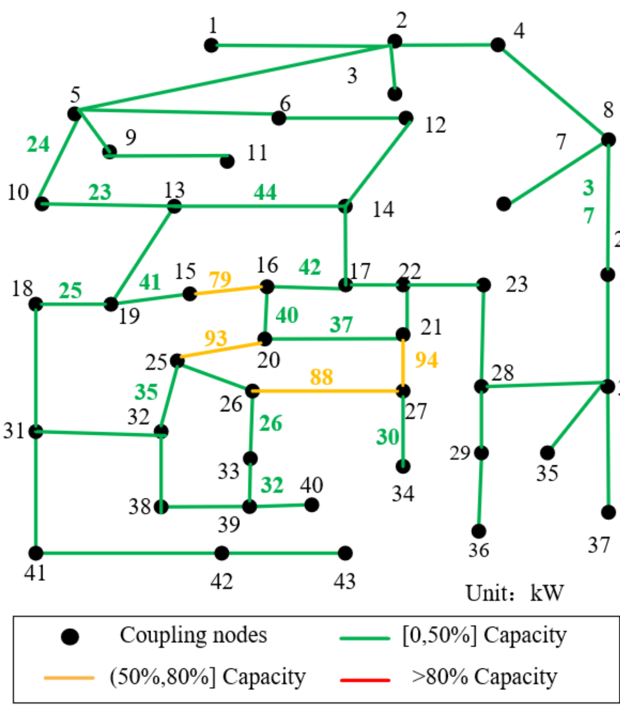

Fig. 8. Network congestion after scheduling.

the charging queuing time for the transportation network.

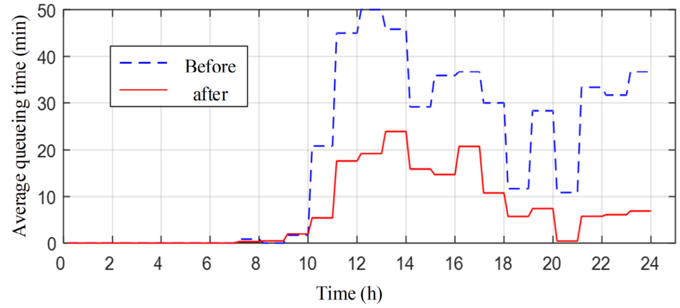

Fig. 9. Hourly average charging queueing time before and after dispatching.

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