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Volt/var regulation exploited from EV charging facilities in urban power distribution systems considering dynamic traffic flow

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ABSTRACT

The booming electric vehicle (EV) charging facilities play a vital role in connecting road transport networks to the urban power grid, as they have internal smart converters with four-quadrant power regulation capability. These converters can provide reactive power to regulate the voltages of urban distribution power grids. Considering the high scarcity of urban spatial resources, there are many restrictions on configuring additional capacitors or other voltage regulating devices. It is of significance to accurately assess the volt/var support capability from the charging facilities on urban grid voltage regulation. This paper constructs a road traffic network model and EV behavior characteristic models for private cars, cabs, and urban service vehicles, respectively. Then, a method for spatial and temporal charging load prediction as well as reactive power flexibility assessment is proposed considering dynamic traffic flow. The assessment results are adopted as boundaries for chargers participating the volt/var regulation of urban power distribution system. The voltage qualification rate indicators are investigated to verify the effectiveness of the proposed regulation method. The results of this paper are helpful for understanding the coupled urban electrified road transportation and power system facilities from a new perspective of volt/var regulation.

Keywords: electric vehicle, dynamic traffic flow, charging facility, volt/var regulation

1. INTRODUCTION

In the context of the global energy transition, the replacement of fuel vehicles by electric vehicles (EVs) is considered as an effective way to solve the problems of fossil energy shortage and environmental pollution[1–3]. Under the influence of the gradual improvement of technology and purchase incentive policies, global sales of EVs continue to rise. According to the statistics of the International Energy Agency, the global annual sales of EVs exceed 10 million units during 2022. In the face of the rapid growth of EV number, demand for charging facilities has become more urgent. By the end of 2022, there has been a total of 2.7 million chargers worldwide[4].

The core device of EV chargers is the bridge converter composed of power electronics, which can control the bi-directional flow of active and reactive power. It has been demonstrated that chargers can provide reactive power compensation to the power system[5–9]. The current power system integrates a large number of distributed renewable energy sources and unstable loads, who lead to voltage instability in the system. Utilizing the reactive power compensation capability of the chargers can exactly achieve volt/var regulation to smooth out voltage fluctuations.

The active-reactive power output model for EV chargers was developed in [10]. The four-quadrant power operating characteristics of the chargers were also utilized for day-ahead optimization with the objective of minimizing the peak-to-valley difference and voltage deviation. Reference [11] proposed a two-stage optimization method to regulate the EV chargers for voltage regulation, thus reducing the use of on-load tap changer. Reference [12] developed a voltage regulation model considering the reactive power response of EV chargers and established a distributed regulation framework based on model predictive control. The volt/var regulation capability of the chargers is highly correlated with their active power output, and these above models just roughly predict the active power demand of EVs, without considering the dynamic traffic flows.

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Studies on charging demand prediction have been carried out. A probabilistic model of EV charging loads was proposed considering the effect of charging start time in [13]. Reference [14] predicted EV arrival rates through hydrodynamic modeling combined with M/M/s queuing theory for charging demand prediction. Reference [15] utilized a Gaussian distribution function for EV charging time and a Weibull distribution function for daily driving time for Monte Carlo sampling based charging loads prediction. Reference [16] determines the probability of arrival of charging stations for EVs from a Markov-chain traffic model and a teleportation approach to predict the charging demand. There are also several studies that utilized big data techniques to combine multiple types of data to learn about EV travel and charging demand characteristics[17–20]. For example, a long short-term memory neural network was developed in [17] for charging demand prediction based on EV data from Beijing, China.

Based on the above studies, this paper develops volt/var regulation technique utilizing EV chargers in urban power distribution systems considering dynamic traffic flow. Firstly, models for road network and 3 types of typical urban EV are built. Next, the spatio-temporal charging load is predicted and reactive power flexibility of EV chargers is assessed. Then, the assessment results are used as boundaries for volt/var regulation of urban distribution systems, and voltage qualification rate indicators are proposed for quantifying the regulation effect. Finally, case studies based on the IEEE 33-bus distribution and road network coupling system are conducted to verify the effectiveness of the proposed technique.

2. ROAD NETWORK AND EV BEHAVIOR MODELS

2.1 Road network model

Graph theory is widely used in urban road network modeling[21]. In this paper, the undirected graph $G(V,E)$ is adopted to describe the topology of the road network, where V is the set of roads in the network and E is the set of nodes in the network. The topology of the road network can be represented by the matrix D in math, and the element d_{ij} in D is determined by (1).

$$d_{ij}=d_{ji}=\begin{cases} l_{ij} & (i,j)\in V \\ 0 & i=j \\ \infty & (i,j)\notin V \end{cases}, \tag{1}$$

where l_{ij} represents the length of roads between directly connected nodes of the network, and ∞ indicates that there is no direct road connection between two nodes.

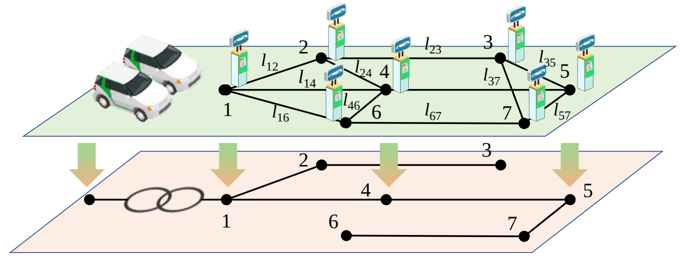

Fig. 1 Road network topology

Table 1 Road network topology matrix

Node	1	2	3	4	5	6	7
1	0	l_{12}	∞	l_{14}	∞	l_{16}	∞
2	l_{12}	0	l_{23}	l_{24}	∞	∞	∞
3	∞	l_{23}	0	∞	l_{35}	∞	l_{37}
4	l_{14}	l_{24}	∞	0	l_{45}	l_{46}	∞
5	∞	∞	l_{35}	l_{45}	0	∞	l_{57}
6	l_{16}	∞	∞	l_{46}	∞	0	l_{67}
7	∞	∞	l_{37}	∞	l_{57}	l_{67}	0

For example, the matrix D of the road network topology shown in Fig. 1 is shown in Table 1. Based on the matrix, the shortest path between the road network nodes can be found by Dijkstra algorithm.

2.2 EV behavioral characteristic models

EV behavior characteristic models for typical urban EVs are developed, and private cars, cabs, and urban service vehicles are considered. The probability distribution curves of their daily travel starting moments are obtained after fitting based on the statistics provided by the National Cooperative Highway Research Program (NCHRP 187)[22].

Private cars are parked for long periods of time and can be charged at all times except during commute driving. Considering the economy of charging, slow charging is generally performed when the SOC is below the threshold SOC_p.

The parking time of cabs is short. Generally, when the remaining SOC is lower than the threshold SOC_c , the cab has fast charging demand. Considering the acceptance ability of different users for the risk of power shortage, the SOC_c is set to obey the uniform distribution between [0.2, 0.3].

Urban service vehicles are usually driven during the day and parked at night. Fast charging demand occurs when SOC is below the threshold SOC_{f1} during working hours. Slow charging demand is generated when the spare time SOC is below the threshold SOC_{f2}.

3. SPATIO-TEMPORAL CHARGING LOAD PREDICTION AND REACTIVE POWER FLEXIBILITY ASSESSMENT

3.1 Dynamic traffic flow and charging load prediction

Urban vehicles are affected by the degree of road traffic congestion during driving so that travel at different speeds on different roads. In this paper, the change of traffic congestion caused by EVs driving into the road is considered to realize the dynamic simulation of traffic flow speed.

Vehicle speed of road r considering dynamic traffic flow is calculated by

$$v_r = \frac{v_{0,r}}{1+\left(\frac{q_r+\Delta q_{EV,r}}{C_r}\right)^{\beta}} \tag{2}$$

where $v_{0,r}$ is the free-flow speed of the road r, which is generally the upper limit speed. q_r is the general traffic flow of the road r; $\Delta q_{EV,r}$ is the change in traffic flow caused by the planned entry of EVs. C_r is the maximum traffic flow of the road r. β is the road resistance factor[23].

With the given origin-destination matrices of the three types of EVs in a day, and default the drivers choose the shortest path to the destination, the set of shortest paths Ψ_R can be obtained by Dijkstra algorithm. Then, the road network topology matrix is utilized to obtain the distance d_r of road r, and the time required for each road segment ΔT_r can be calculated by

$$\Delta T_r = \frac{d_r}{v_r}, \tag{3}$$

The total driving time from origin to destination can be calculated by

$$T_{total} = \sum_{r\in\Psi_R} \Delta T_r , \tag{4}$$

Based on the EV charging characteristics presented in 2.2, determine whether the EV needs to be charged when it is located at each node. The calculation on each road segment is performed one by one to finally obtain the fast charging and slow charging requirements for each node for 24h in a day.

3.2 Reactive flexibility assessment of charging facilities

The core element of the charging facility is the bridge converter, and there exists an upper limit to the total power passing through the bridge converter[24]. Therefore, the reactive power flexibility of the charger is directly related to its active power output, and the maximum available reactive power capacity is shown in (5) and Fig. 2[25].

$$Q_{i,\max} = \sqrt{S_i^2 - P_i^2} , \tag{5}$$

where S_i is the rated total power of charger i, and P_i is the active power output from charger i.

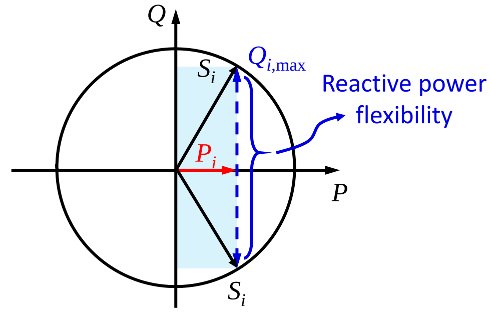

Fig. 2 Reactive flexibility of EV charger

The reactive power flexibility of a power system bus is an aggregation of the reactive power flexibility of the chargers connected to it, denoted as

$$Q_{j,\max} = \sum_{i\in\Psi_j} Q_{i,\max} , \tag{6}$$

where $Q_{j,\max}$ is the maximum available reactive capacity of bus j and Ψ_j is the set of chargers connected to bus j.

4. POWER DISTRIBUTION SYSTEM VOLT/VAR REGULATION CONSIDERING EV CHARGERS

4.1 Volt/var regulation model

The volt/var regulation model is based on improved AC optimal power flow (OPF). The minimizing the sum of voltage deviations at each bus of the whole network has been added as an objective function to the OPF, as shown in (6).

$$\min J = \sum_{j=1}^{N_{bus}} \left(V_j - V_{rated}\right)^2 , \tag{7}$$

where N_{bus} is the total number of buses. V_j is the voltage of bus j. V_{rated} is the rated voltage.

The constraints of the volt/var regulation model include available reactive power capacity constraints, distribution network voltage constraints, line capacity constraints and power flow constraints.

$$\left|Q_j\right| \le Q_{j,\max} , \tag{8}$$

$$V_{j,\min} \le V_j \le V_{j,\max} , \tag{9}$$

$$S_{jk,\min} \le S_{jk} \le S_{jk,\max} , \tag{10}$$

$$S_{jk} = \sqrt{P_{jk} + Q_{jk}} , \tag{11}$$

$$P_j^{load} + V_j \sum_{k=1}^{N_{bus}} V_j \left(G_{jk}\cos\theta_{jk} + B_{jk}\sin\theta_{jk}\right) = 0 , \tag{12}$$

$$-Q_j + Q_j^{load} + V_j \sum_{k=1}^{N_{bus}} V_k \left(G_{jk}\sin\theta_{jk} - B_{jk}\cos\theta_{jk}\right) = 0 , \tag{13}$$

Eq. (8) and Eq. (9) are the available reactive power capacity constraint and voltage constraint of bus j, respectively. $V_{j,\min}$ and $V_{j,\max}$ denote the lower and upper limit of voltage of bus j, respectively. Eq. (10) is the capacity constraint of line between bus j and bus k. $S_{jk,\min}$ and $S_{jk,\max}$ denote the lower and upper limit of the line capacity, respectively. S_{jk} , P_{jk} and Q_{jk} denote the apparent power, active power, and reactive power from bus j to bus k, respectively. Eq. (12) and Eq. (13) are the power flow constraints, where P_j^{load} and Q_j^{load} denote the active and reactive power of the load at bus j, respectively; θ_{jk} denotes the difference in the phase angle of the voltage between bus j and bus k; G_{jk} and B_{jk} denote the conductance and susceptance values of the j^{th} row and k^{th} column of the nodal admittance matrix, respectively.

For the proposed regulation model with OPF as the core, the interior point algorithm is the efficient solution method. The solver such as IPOPT can be called to solve the optimization[26].

4.2 Voltage qualification rate assessment

In order to quantify the effect of volt/vat regulation, two voltage qualification rate indicators are proposed. These include average voltage deviation indicator I_d and voltage quality rate indicator I_q, which are calculated by (14) and (15), respectively.

$$I_d = \frac{1}{N_h}\sum_{h=1}^{N_h}\frac{1}{N_{bus}}\sum_{j=1}^{N_{bus}}\left|V_{h,j} - V_{rated}\right|, \tag{14}$$

where $V_{h,j}$ is the voltage of bus j at hour h and N_h is the total number of hours included in the statistics.

$$I_q = \frac{100\%}{N_h}\sum_{h=1}^{N_h}\frac{1}{N_{bus}}\sum_{j=1}^{N_{bus}} R_{h,j}\ , \tag{15}$$

where R_h is the voltage quality mark for the h^{th} hour, calculated as:

$$R_{h,j} = \begin{cases} 1, & if\ \left|V_{h,j} - V_{rated}\right| \le 0.04V_{rated} \\ 0, & otherwise \end{cases}. \tag{16}$$

5. CASE STUDY

In this section, a road network coupled with an IEEE 33-bus system is constructed. The road network has a total of 32 nodes, corresponding to nodes 1-32 of the power system, respectively. The topologies of the power system and the road network are shown in Fig. 3 and Fig. 4. Each road node is equipped with 40 slow chargers and 20 fast chargers.

In the case studies, there are 200 private cars, cabs, and urban service vehicles. At the initial moment, the number of EVs at each node is shown in Fig. 5.

Based on the dynamic traffic flow and charging demand prediction method proposed in this paper, the charging power at each node for 24 hours is obtained. The fast charging and slow charging power are shown in Fig. 6 and Fig. 7, respectively.

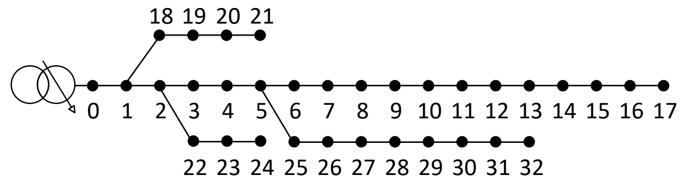

Fig. 3 Topology of power system

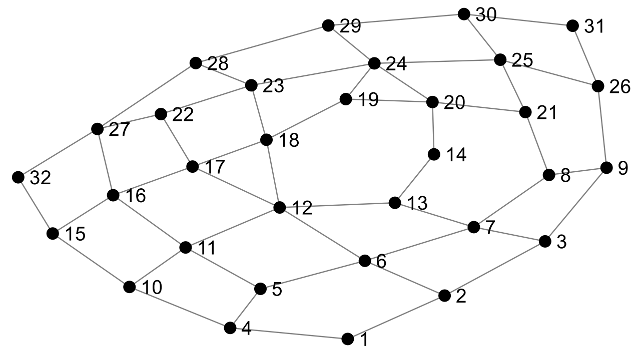

Fig. 4 Topology of road network

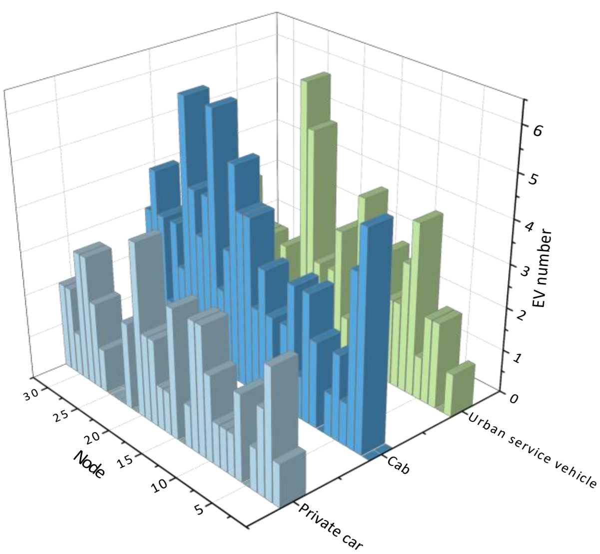

Fig. 5 The initial number of EVs at each node

It can be seen that most of the charging loads during the daytime are dominated by fast charging, while the charging loads during the nighttime are dominated by slow charging. Fig.8 further shows the number of different types of EVs charged at different times.

More conclusions are obtained from Fig. 8. The fast charging power during the daytime is mainly caused by cabs. This is because cabs are always on the move and consume more power, which leads to charge in the middle of the day. And in order not to affect working, they all choose fast charging. Besides, there are also a small number of private cars that charge during the day. Because they have a long commute to work, their initial

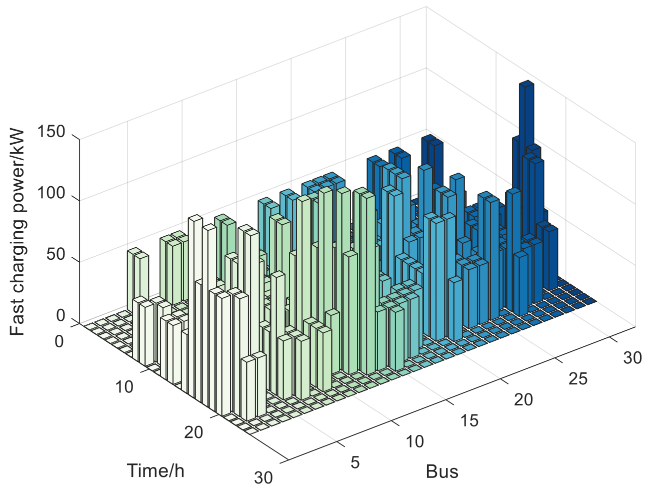

Fig. 6 Fast charging power

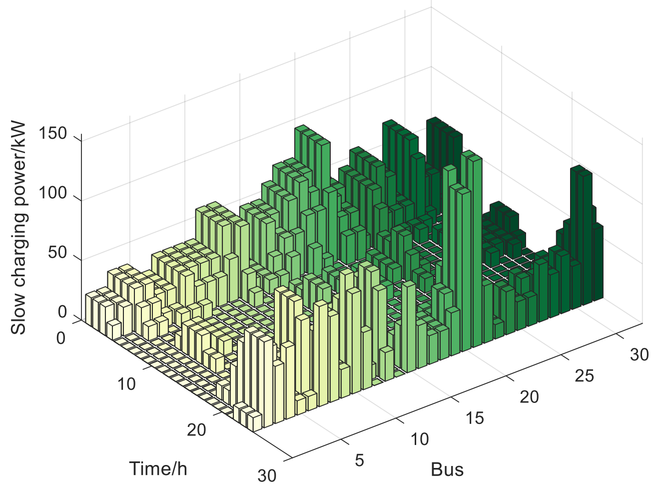

Fig. 7 Slow charging power

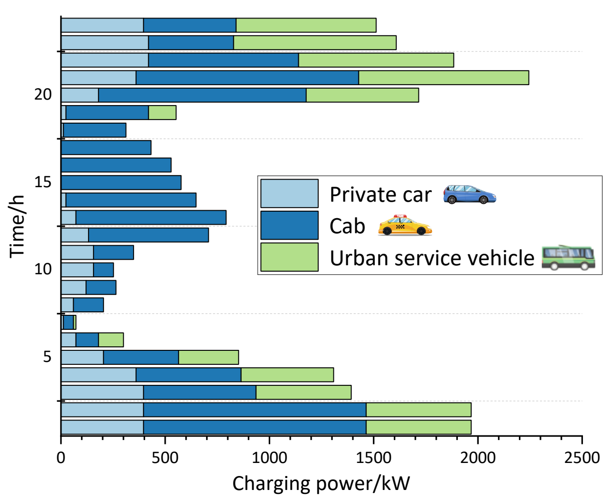

Fig. 8 Charging data of different types of EVs

charge is not sufficient for the return trip. As a result, they charge during daytime working hours. Urban service vehicles are generally charged at night.

Based on the predicted charging power, the voltage at each bus of the distribution network is calculated in 24 hours, as shown in Fig. 9.

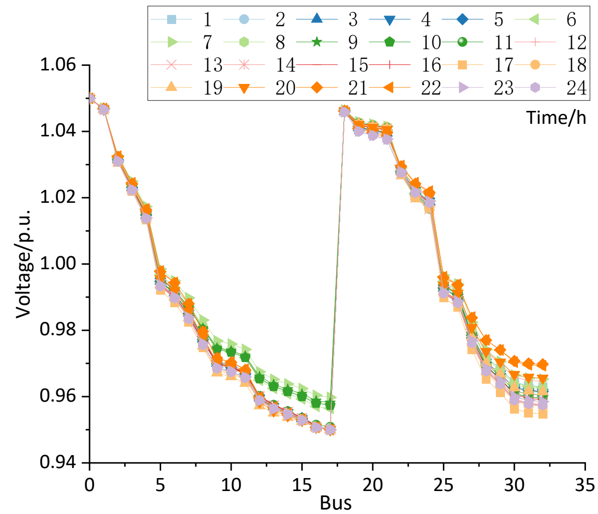

Fig. 9 Bus voltage in 24 hours

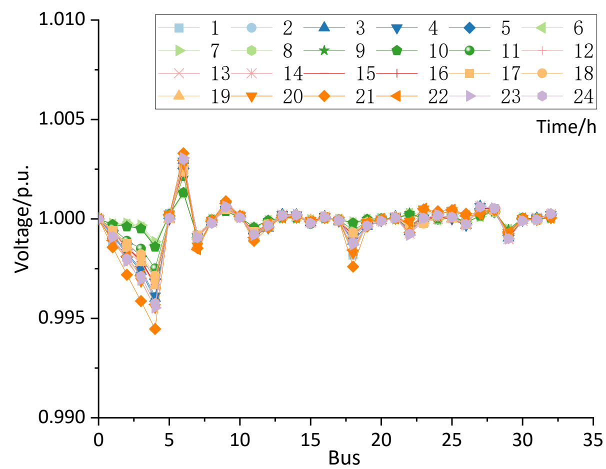

Fig. 10 Bus voltage after volt/var regulation

Table 2 Voltage qualification indicators

	Before regulation	After regulation
I_d	0.031079	0.000528
I_q	70.1%	100%

The results show that the voltage fluctuation of the distribution network is large and the voltage decrease from the front to the end. The front-side voltage is about to exceed the upper limit, while the back-side voltage is about to exceed the lower limit, and there is an urgent need to take means to regulate the voltage. After adjustment using the volt/var regulation method proposed in this paper, the voltage at each bus of the distribution network in 24 hours is shown in Fig. 10.

The results show that after volt/var regulation, the voltage at all buses is within the range of [0.994, 1.004]. The fact that the voltage is close to the rated voltage implies an improvement in the quality of power supply and also helps to reduce the network losses. The voltage qualification indicators before and after the regulation is shown in Table 2.

After regulation, id is reduced to 0.0016 times the original value, indicating that the deviation of the bus voltages from the rated value is substantially reduced. iq grows from 70.1% to 100%, indicating that the voltage at all nodes is at a good quality level, reflecting the effectiveness of the present method.

6. CONCLUSIONS

This paper exploits the volt/var regulation ability of EV charging facilities in urban power distribution systems considering dynamic traffic flow. Firstly, a road network model based on graph theory and EV behavioral characteristic models for private cars, cabs and urban service vehicles are built. Then, a method for spatio-temporal charging load prediction and reactive power flexibility assessment is proposed based on EV origin-destination matrix and Dijkstra dynamic path search. The assessment results are used as boundaries for volt/var regulation of urban distribution systems, and voltage qualification rate indexes are proposed for quantifying the regulation effect. Finally, volt/var regulation case studies based on the IEEE 33-bus distribution and road network coupling system with the participation of EV chargers are carried out.

The results show that the technique proposed in this paper is accurate in predicting the demand for charging of three types of EV. The volt/var regulation method can effectively improve the voltage quality at each node of the distribution network, as evidenced by the significant changes in the voltage qualification rate indicators.

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