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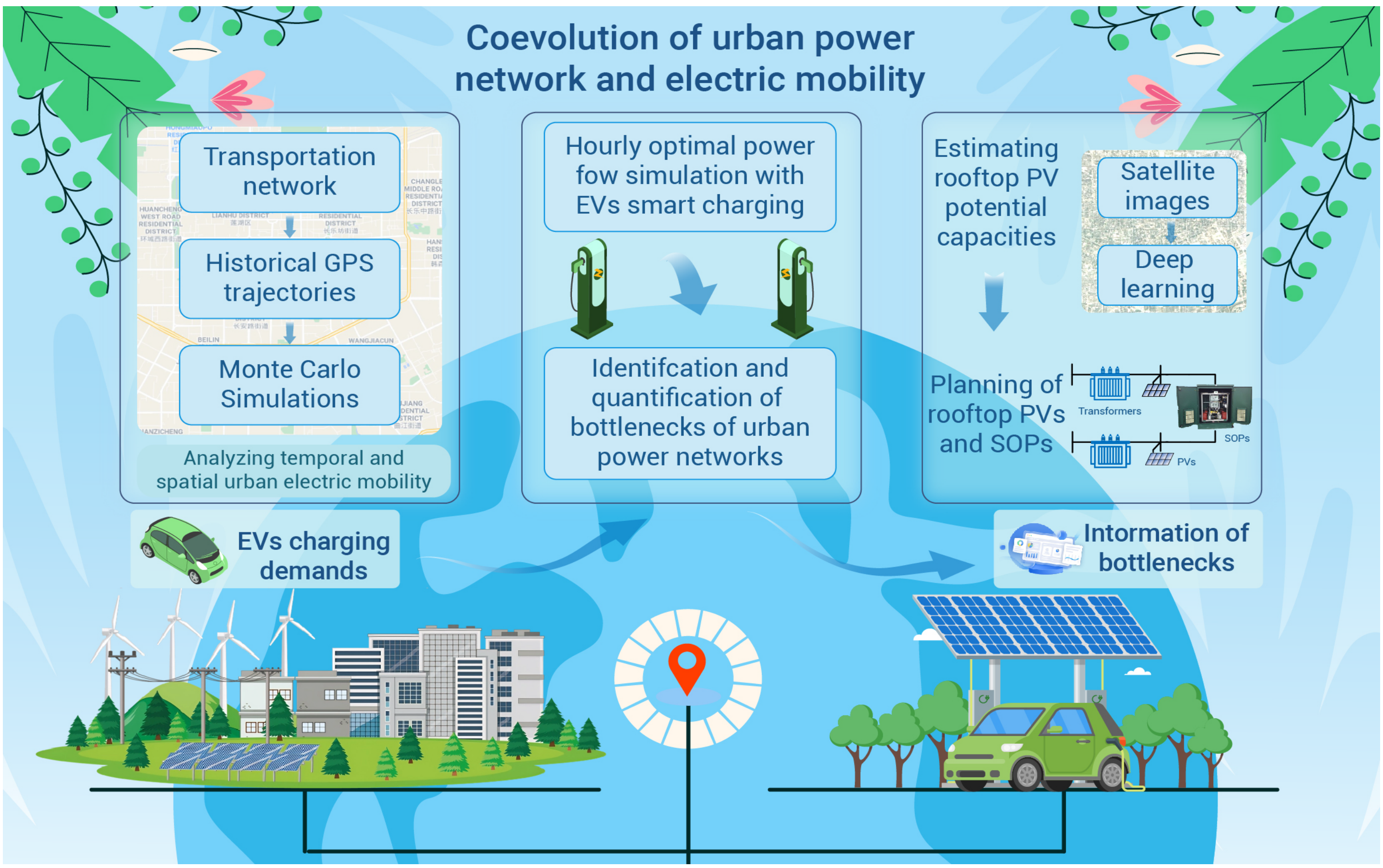
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Data-driven approach identifies and quantifies bottlenecks in urban power networks (UPNs) due to electric vehicle adoption.
- Finds UPN bottlenecks in Xi'an will emerge by 2026, with smart charging first applied to address them.
- Proposes UPN evolution with rooftop photovoltaics (PVs) and soft open points (SOPs) starting in 2032.
- Xi'an's UPNs can support China's EV integration target without large-scale network upgrades using the proposed measures.
- Ensures sustainable co-evolution of UPNs and electric mobility through strategic interventions.

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Urban power networks (UPNs) are crucial for decarbonization of urban transport sector through electrifying mobility. Serious concerns have been raised that a large-scale adoption of electric vehicles (EVs) may bring significant uncertainties and spatial imbalance to UPNs. Here, we present a data-driven approach to identify and quantify bottlenecks of UPNs with the development of electric mobility and further propose an effective solution to achieve sustainable co-evolution of the UPNs and electric mobility. Taking a megacity, Xi'an, China, as a representative case, we find that the earliest UPNs' bottlenecks would emerge by 2026. EVs smart charging will be firstly applied to eliminate bottlenecks in 2026, followed by power networks evolution with rooftop photovoltaics (PVs) installation and soft open points (SOPs) starting from 2032. Based on those measures, UPNs in Xi'an city are able to support the achievement of China's EVs integration target even without large-scale urban electrical network upgrade.

INTRODUCTION

Global efforts are taken to achieve rapid emissions reductions via large-scale electric vehicles (EVs) integration.[1-5] In China, for example, in first seven months of 2025, EVs have accounted for about 45% market share of the total new car sales.[6] It is also envisioned that the figure will reach about 75% by 2030 and about 90% by 2035.[7] Urban power networks (UPNs) are under a huge pressure of enabling and facilitating such electrification and decarbonization ambitions.[8-10] The concern naturally arises: are the current UPNs ready?

There has been increasing evidence on the significant impacts of EVs integration on the operation of UPNs, even at the modest EVs adoption level.[11-13] The local residential load curve is completely reshaped by the EVs charging behavior.[14-16] For a typical residential feeder circuit of 150 homes at 25% EV adoption, the analysis indicated that the local peak load would increase by approximately 30%,[17] which would bring a heavy burden to distribution transformers.[18] In addition, the influences of spatial mobility of EVs on the physically-constrained UPNs need to be better understood.[19,20] The dynamic traffic patterns will profoundly affect the spatial distribution of EVs charging demands and further aggravate the transformers' loading imbalance.[21-23] Hence, it is imperative to identify the conceivable bottlenecks of the UPNs with the development of urban electric mobility and find a way to break through them.[24-26]

To address the problem, on one hand, EVs smart charging[2,27-31] is critical to be implemented, of which the benefits include flattening load curves,[32] reducing phase imbalance,[33] and increasing the consumption of renewables.[34] On the other hand, a comprehensive method that puts the UPNs' future potential power supply capabilities at the center of analysis is needed. The focus on this topic over a decade facilitate the understanding of how the planning of renewable energy sources[35,36] and network reinforcement,[37-40] such as the capacity expansion of substations and lines, continuously support the decarbonized urban electrification. However, the above methods largely ignore the practical limits. For example, the availability of lands required to construct photovoltaics (PV) panels has not been comprehensively considered. Expansion of centralized PV requires a large quantity of land area, which is neither infinite nor free.[42-44] Distributed rooftop PV seems to be an alternative, but its potential capacity is yet bounded by the available amount of urban rooftop areas. Moreover, UPNs in urban areas with high population density normally have limited opportunities for large-scale upgrade.[45,46] These constraints are primarily due to spatial limitations,[47] exorbitant costs of infrastructure overhaul,[48] and the critical need to avoid prolonged service disruptions to a large number of residents and businesses.[49]

Recently, soft open points[50-53] (SOPs), a new type of power electronic devices, draws a huge attention due to its capabilities of enhancing the power supply capability of UPNs.[54-58] Compared to the traditional capacity expansion of bulk substations taking several years,[59-61] the SOPs simply replaces the normally-open point of UPNs within a few months,[62-64] which endows SOPs with broad application prospect in the urban areas. From the electricity infrastructure perspective, the value of SOPs in breaking through UPNs' bottlenecks needs to be better explored.

Therefore, electrifying transport sector and upgrading of UPNs are closely related,[65-68] and a co-evolution pathway capturing the interactions between both is essential to be achieved. There is a conflict between the radical EVs integration in the short term and the upgrade planning of UPNs in a longer term.[69-72] Although the goal of sustainable and coordinated development has been widely accepted, there exists a paucity of concepts and tools to work towards it.[73]

Targeting the above-mentioned gap, we propose a sustainable solution to orchestrating the co-evolution pathway of urban electric mobility and UPNs via synthesizing the analysis of trajectory-based mobility data and the strategically unlocking the potential of UPNs' power supply capabilities with novel SOPs. We take main urban areas of Xi'an, China, as a case study, and design a data-driven approach as depicted in Figure 1. We firstly simulate the EVs charging patterns based on the analysis of urban mobility data and the Monte Carlo method. Then, we identify and quantify the potential bottlenecks of UPNs in Xi'an by formulating the hourly optimal power flow simulation with EVs smart charging. Further, we estimate the potential capacity of

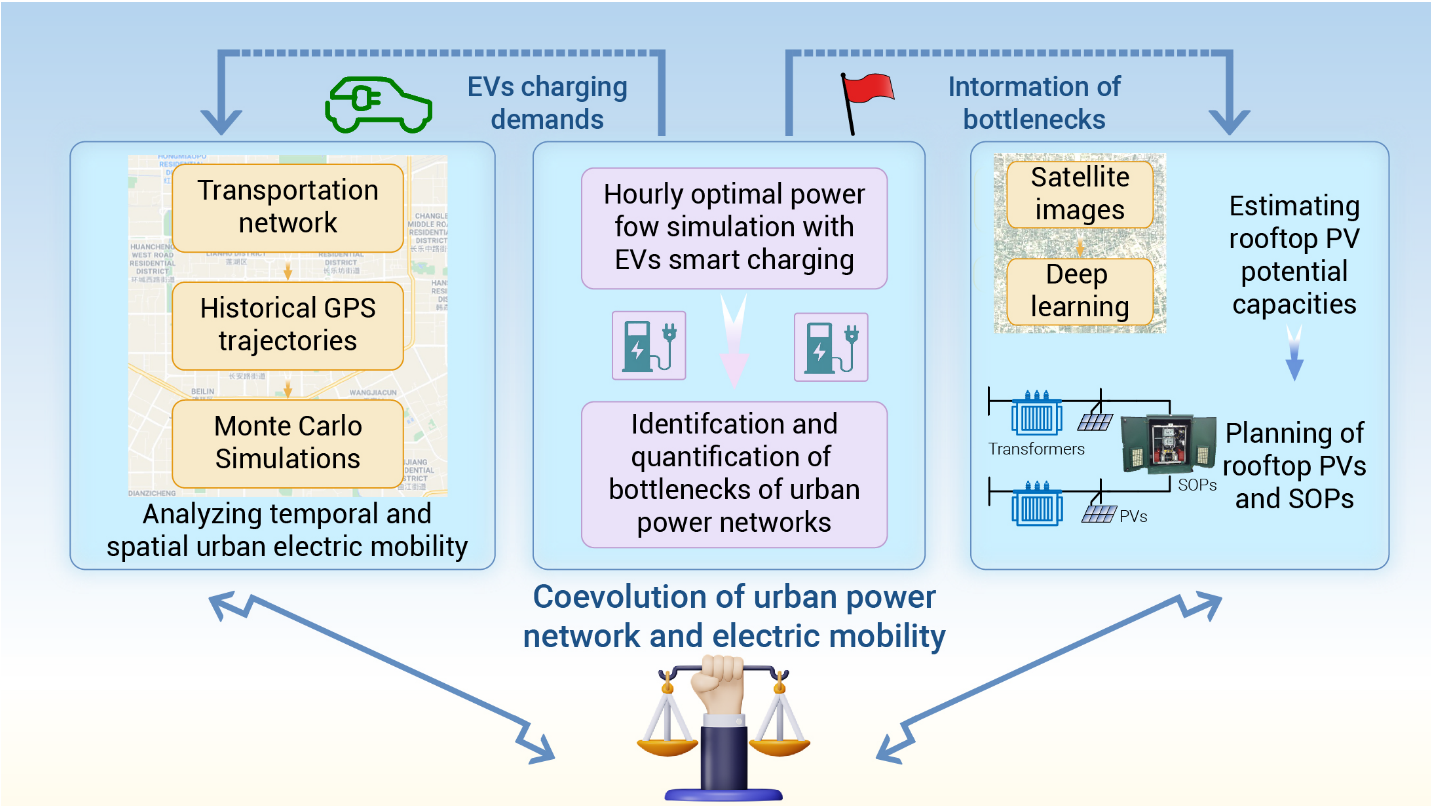

Figure 1. The coevolution of urban power networks and electric mobility.

rooftop PV in Xi'an by a deep learning-based method. Based on results obtained from above three steps, we determine the best location and capacity of rooftop PVs and SOPs installations to eliminate potential bottlenecks. Furthermore, we analyze the urban decarbonization performance with different speeds of EVs mobility and rooftop PVs development in the next 10 years.

MATERIALS AND METHODS

Vehicle growth prediction in Xi'an

Xi'an is the capital city of Shaanxi Province in China with a high population density and a large vehicle stock. To analyze the EV charging characteristics of Xi'an, firstly we project the incremental number of vehicles in the following 11 years based on the total number of vehicles in Xi'an from 2012 to 2024.[74-77] According to the prediction of China Automotive Engineering Research Institute, we set up the 50% market share of EVs in 2025, 75% in 2030, and 90% in 2035.[7] The market shares of EVs in other years are obtained by the logistic regression, shown in Figure 2A Based on the assumption of 5% scrapped rate of vehicles, Figure 2B displays the predictions of the number of electric and gasoline-based vehicles in Xi'an in 2035, which amounts to 7.93 million and 4.85 million respectively.

GPS trajectories of urban mobility

We selected 9.5km*8.8km urban area for analysis, which is mainly for residents and third-industry businesses. The EVs charging characteristics in this urban area were simulated based on the DiDi open dataset[78] with historical global positioning system (GPS) trajectories of ride-hailing orders in the urban areas of Xi'an. Each data in the dataset includes the anonymous driver ID, order ID, longitude, latitude and time stamp. For example, we can depict one of the drivers' trajectories in the transportation network of Xi'an, as illustrated in Figure 2C Meanwhile, we can calculate the distribution of when a travel starts which indicates that travelling demands usually peak between 3pm to 10pm as shown in Figure 2D

The dataset reveals different traffic patterns for work-related vehicles and home-based vehicles in Xi'an. For the work-related EVs, such as taxi and business cars, the whole-day trajectories can be directly sampled from the dataset. We assume that travel patterns within the urban transport system would remain consistent, no matter the vehicles are electric or gasoline-based. Then, we can track the state of charge (SoC) of each trajectory and predict the time and location of its potential charging.[42] For the home-based EVs, we can calculate the probability of which subarea an EV origins from in the morning peak, as shown in Figure 2E

To better schedule the home-based EVs charging profiles, we optimize the charging profiles considering the hourly variations of traditional power loads and capacities of transformers. The aim is to alleviate the impacts of EVs charging on UPNs operation and minimize the necessary requirement of UPNs reinforcement. To this end, instead of directly simulating home-based EV charging profiles, we employ the EV aggregator model and use the Monte Carlo method to simulate its parameters, including stored electricity and maximum charging power. Then, the EV aggregator model is incorporated in the optimal power flow model to determine the optimal charging profiles.

Monte Carlo simulations[79,80] are applied to generate the charging demands of work-related EVs and model the charging characteristics for home-based EVs based on the statistical distributions as described in the main text. Then, the charging characteristics of home-based EVs are formulated and aggregated to represent the charging loads.

For the work-related EVs, we first eliminate the GPS trajectories that last for less than 8 hours from the dataset for ruling out the part-time work-related vehicles. After that, we set the initial SoC at the start of each trajectory as 0.8 and the lower bound of SoC is 0.2. On that basis, we can track the SoC of each trajectory to determine the subarea and time of the charging. Once the charging is completed, we renew the SoC to 0.8 and continue the examination. The fast charging power is set as 100kW, and the battery capacity of EVs is 32kWh. Then, according to the total number of work-related EVs, trajectories with charging behavior are sampled, and total charging profiles of work-related EVs are obtained.

For the home-based EVs, we first sample the arrival/departure subarea and hours based on the statistical distributions generated for the historical GPS trajectories dataset. Given the information, an EV aggregator model is adopted to describe the collectively charging schedule of individual home-based EVs under the slow-charging mode. Instead of optimizing the charging profile of each EVs, the EV aggregator model optimizes the charging profile of the entire home-based EVs fleet, which can be incorporated into the

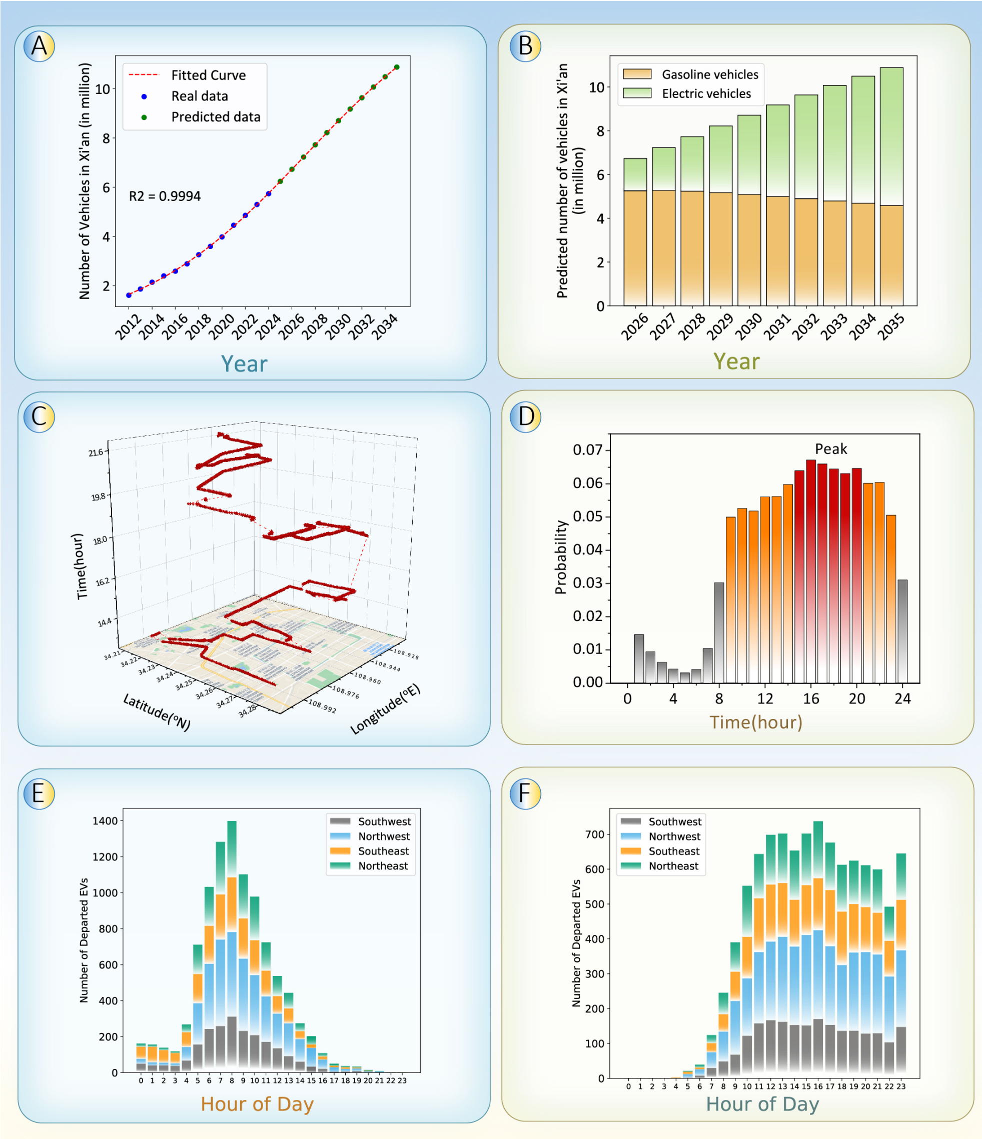

Figure 2. Features of EVs in Xi'an city.

optimal power flow model of UPNs.

In specific, Monte Carlo simulation is applied to determine the parameters of the EV aggregator model at hour t in subarea i such as maximum charging power $P^{ch,\max}_{t,i}$, maximum stored energy $E^{\max}_{t,i}$, stored energy in arriving EVs $E^{arrive}_{t,i}$ and stored energy in leaving EVs $E^{leave}_{t,i}$, which are formulated as follows:

$$P^{ch,max}_{t,i} = \sum_{n=1}^{N_{t,i}} p^{ch,max}_{i,n}, \forall t,i \tag{1}$$

$$E^{\max}_{t,i} = \sum_{n=1}^{N_{t,i}} e^{max}_{i,n}, \forall t,i \tag{2}$$

$$E^{arrive}_{t,i} = \sum_{n=1}^{N^{arrive}_{t,i}} e^{arrive}_{i,n}, \forall t,i \tag{3}$$

$$E^{leave}_{t,i} = \sum_{n=1}^{N^{leave}_{t,i}} e^{leave}_{i,n}, \forall t,i \tag{4}$$

Here, N^t_i represents the total number of EVs at hour t in subarea i. $N^{arrive}_{t,i}$ and $N^{leave}_{t,i}$ indicate the number of arriving and leaving EVs at hour t in subarea i. In addition, $p^{ch,max}_{i,n}$, $e^{max}_{i,n}$, $e^{arrive}_{i,n}$ and $e^{leave}_{i,n}$ are the maximum charging power, maximum stored energy, stored energy in arriving EV and stored energy in leaving EV, respectively. On that basis, we have the following constraints of the EV aggregator model:

$$E_{t,i} = E_{t-1,i} + p^{ch}_{t,i} + E^{arrive}_{t,i} - E^{leave}_{t,i}, \forall t,i \tag{5}$$

$$p^{ch}_{t,i} \leqslant P^{ch,\max}_{t,j}, \forall t,i \tag{6}$$

$$E_{t,i} \leqslant E^{\max}_{t,i}, \forall t,i \tag{7}$$

$$E_{t,i} \geqslant E^{leave}_{t+1,i}, \forall t,i \tag{8}$$

where constraint (5) describes the relationship between the stored energy of EVs and the charging power. Constraints (6) and (7) limit the maximum value of charging power and stored energy. Finally, constraint (8) ensures the satisfaction of trip requests of leaving EVs. We note that the charging power $p^{ch}_{t,i}$ are the decision variables determined in the hourly optimal power flow to optimize the home-based EVs charging profiles.

Deep learning-based estimation of rooftop PV potential

So far, limited publicly accessible rooftop data for urban areas is available in China.[43] Here, we adopt open-access data sources, i.e., Google Earth satellite (GES) images, to quantify the potential rooftop area in Xi'an urban areas. In accordance with the topology of UPNs in Xi'an, we divide the selected area into 16 subareas. To extract the rooftop information from the GES images efficiently, we utilize the deep-learning based semantic segmentation method.[81,82] It is modelled as a classification problem of pixels with semantic labels. In addition, deep neural networks are applied to enhance the accuracy of semantic segmentation and improve its generalization ability.

Specifically, we first randomly select the satellite images covering 15% of the entire area and manually label the pixels representing rooftop. With the data augmentation procedure, the training dataset is formed. Then, we can construct the loss function of semantic segmentation as follows:

$$loss = -\frac{1}{N}\sum_{i=1}^{N} y_i \log(\sigma(\hat{y}_i)) + (1-y_i)\log(1-\sigma(\hat{y}_i)) \tag{9}$$

where N indicates the number of pixels in one batch, and y_i represents the labelled categorization of the i th pixel. In particular, the pixel representing rooftop area has y_i=1, otherwise y_i=0. $\sigma(\cdot)$ represents the sigmoid function for normalizing the output of the neural network $\hat{y}_i$. In addition, the convolutional layers in the neural network can be formulated as:

$$F^{l+1}(p,q) = \sum_{i=1}^{D}\sum_{j=1}^{D} w^l(i,j) F^l(p+i, q+j) + b^l \tag{10}$$

where $F^l(\cdot)$ is the feature extracted by the convolutional layer l and input fed to the layer l+1. w^l and b^l represent the trainable parameters of filter l. p, q, i and j determine the position of elements in the input layer and filter. D denote the size of the filter. In general, convolutional calculation is inspired by biological processes[79] in that the local pattern between neurons resembles the organization of the animal visual cortex. The detailed process of convolutional calculation is illustrated in Supplementary.

For deep learning-based methods, the performance of models relies on the quality and quantity of the training data.[83-85] Here, we pre-process and augment the GES images in the training dataset. First, the gamma correction

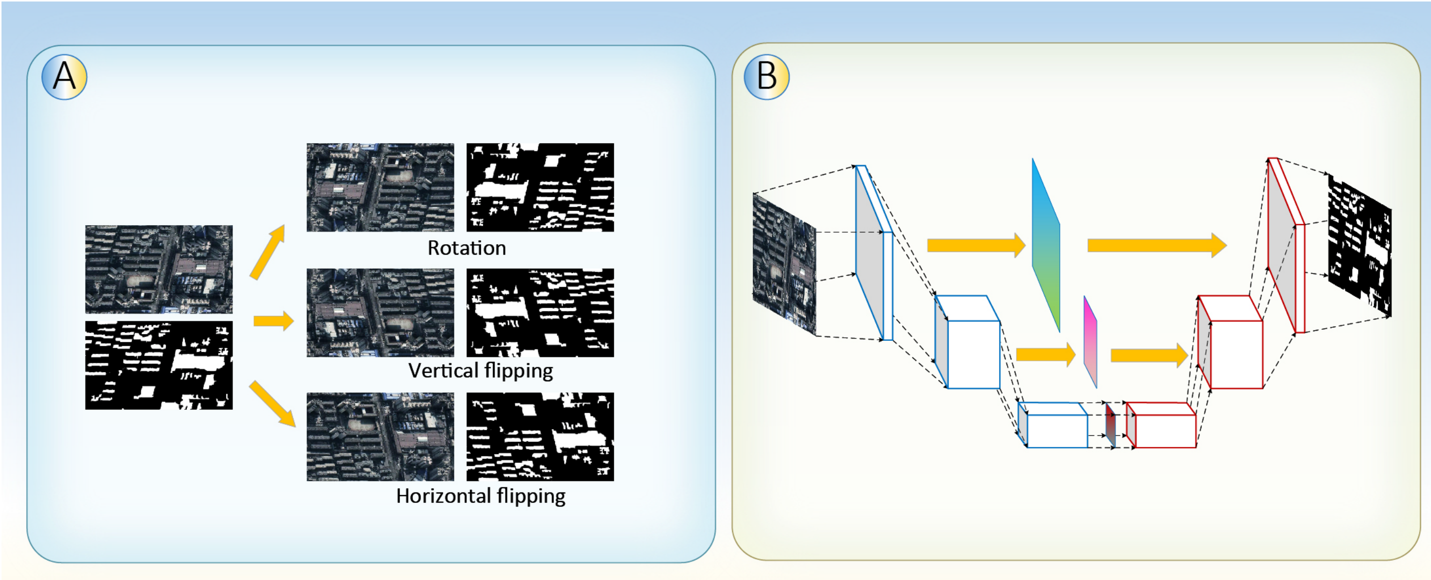

Figure 3. Deep learning-based estimation of rooftop PV potential capacity in Xi'an city.

and contrast limited adaptive histogram equalization are performed to adjust the brightness and sharpness levels of the GES images. Then, a drawing tool is applied to labeling the rooftop in the adjusted GES images in the training dataset. Finally, data augmentation is conducted to generate more training data via image rotation and flipping, as shown in Figure 3A. There is a total of 62 GES images in the training dataset, and their sizes are 650*420 pixels.

The training of semantic segmentation is implemented based on the well-known U-Net structure.[86-88] The U-Net structure consists of two parts, a down-sampling path to extract features, and a symmetric up-sampling path that enables accurate localization. The down-sampling part has the convolution layers, and the up-sampling uses transpose convolution layers, as shown in Figure 3B. Features from the down-sampling part of the network are copied to the up-sampling part to avoid losing pattern information. Finally, a unit-size convolution layer generates a segmentation that classifies each pixel of the input image.

Potential bottlenecks identification of urban power networks

We utilize the hourly optimal power flow simulation of UPNs in Xi'an city to quantify the potential bottlenecks in the next 10 years from 2026 to 2035. Incorporating the EV aggregator model, the hourly UPN simulation minimizes the total cost of UPNs' operation. Apart from the conventional power flow constraints such as active and reactive power balance, the constraints of SOPs operation are also incorporated in the optimal power flow model.

The decision variables at hour t in subarea i include the home-based EV charging power $p_{t,i}^{ch}$, the active $p_{t,i,j}^{line}$ and reactive power $q_{t,i,j}^{line}$ on the line connecting subareas i and j, the active $p_{t,i}^{0}$ and reactive $q_{t,i}^{0}$ power transmitted from the upper-level grid, the active $p_{t,i,n}^{SOP}$ and reactive power $q_{t,i,n}^{SOP}$ of nth SOPs terminals, the power loss $p_{t,i,n}^{loss}$ of SOPs, the increasing capacity $c_i^{PV,add}$ of rooftop PV and the slack capacity c_i^{slack} of transformer in subarea i.

The objective function aims to minimize the overall operation cost including the cost of purchasing the active and reactive power from the upper-level grid and the penalty of the transformer overload, formulated as follows:

$$\min\sum_{i=1}^{I}\left(\sum_{t=1}^{T}\lambda^{p}p_{t,i}^{0}+\lambda^{q}q_{t,i}^{0}\right)+\lambda^{ol}c_i^{slack} \tag{11}$$

where λ^{p}, λ^{q} and λ^{ol} indicate the price of active and reactive power and penalty coefficient of overload, respectively. The active and reactive power balances are ensured by constraints as follows:

$$p_{t,i,j}^{line}-\sum_{(j,k)\in L}p_{t,j,k}^{line}=p_{t,j}^{load}+p_{t,j}^{ch,fast}+p_{t,j}^{ch}-p_{t,j}^{PV}-p_{t,j,n}^{SOP},\forall i,t \tag{12}$$

$$q_{t,i,j}^{line}-\sum_{(j,k)\in L}q_{t,j,k}^{line}=q_{t,j}^{load}+q_{t,j}^{ch,fast}+q_{t,j}^{ch}-q_{t,j,n}^{SOP},\forall i,t \tag{13}$$

where $p_{t,j}^{load}$, $q_{t,j}^{load}$, $p_{t,j}^{ch,fast}$ represent the traditional active loads, reactive loads and un-schedulable fast charging loads of work-related EVs. The slow charging loads of home-based $p_{t,j}^{ch}$ is optimized subject to constraints (7)-(10). $p_{t,j}^{PV}$ indicates the active power of rooftop PV, which is limited by the PV capacity in subarea i:

$$0\leqslant p_{t,i}^{PV}\leqslant\delta_{t,i}^{PV}\left(c_i^{PV}+c_i^{PV,add}\right) \tag{14}$$

$$c_i^{PV}+c_i^{PV,add}\leqslant C_i^{PV},\forall i \tag{15}$$

$$\sum_{i=1}^{I}c_i^{PV,add}=C_{add}^{PV} \tag{16}$$

where $\delta_{t,i}$ is active power output of unit PV capacity and c_i^{PV} is the capacity of installed PV. C_i^{PV} represents the limit of total PV capacity in subarea i, which is determined by the deep-learning based semantic segmentation method. Finally, C_{add}^{PV} is the given increasing capacity of rooftop PV.

In addition, the operation constraints of SOPs are illustrated as follows:

$$P_{t,i,n}^{SOP}+P_{t,j,n}^{SOP}+P_{t,i,n}^{loss}+P_{t,j,n}^{loss}=0,\forall t,n \tag{17}$$

$$p_{t,i,n}^{loss}=\eta_{t,i,n}^{loss}\sqrt{\left(p_{t,i,n}^{SOP}\right)^{2}+\left(q_{t,i,n}^{SOP}\right)^{2}},\forall t \tag{18}$$

$$p_{t,j,n}^{loss}=\eta_{t,j,n}^{loss}\sqrt{\left(p_{t,j,n}^{SOP}\right)^{2}+\left(q_{t,j,n}^{SOP}\right)^{2}},\forall t \tag{19}$$

$$Q_{t,n,\min}^{SOP}\leqslant q_{t,i,n}^{SOP}\leqslant Q_{t,n,\max}^{SOP},\forall t \tag{20}$$

$$\sqrt{\left(p_{t,i,n}^{SOP}\right)^{2}+\left(q_{t,j,n}^{SOP}\right)^{2}}\leqslant S_{i,n}^{SOP},\forall t \tag{21}$$

$$\sqrt{\left(p_{t,i,n}^{SOP}\right)^{2}+\left(q_{t,j,n}^{SOP}\right)^{2}}\leqslant S_{i,n}^{SOP},\forall t \tag{22}$$

where constraint (17) ensures the active power balance of SOPs. Constraints (18)-(19) describe the incurred power losses of the SOPs operation, and constraint (20) defines the boundaries of reactive power output. In addition, Constraints (21) - (22) define the capacity the of SOPs.

Finally, the power line and transformer capacity constraints are shown as follows:

$$\sqrt{\left(p_{t,i,j}^{line}\right)^{2}+\left(q_{t,i,j}^{line}\right)^{2}}\leqslant S_{i,j}^{line},\forall t \tag{23}$$

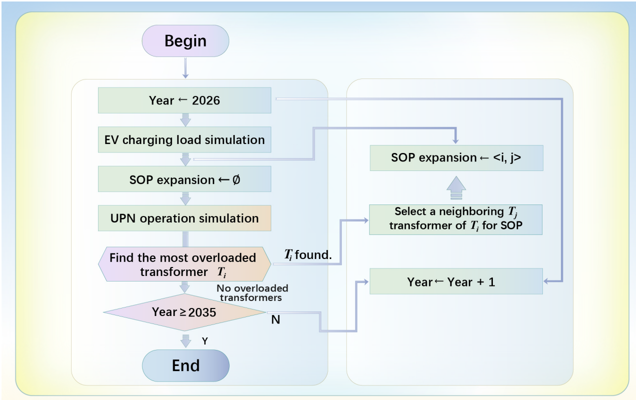

Figure 4. Flow chart of the SOPs planning.

$$\sqrt{\left(p_{t,i,j}^{line}-\sum_{(j,k)\in L}p_{t,j,k}^{line}\right)^2+\left(q_{t,i,j}^{line}-\sum_{(j,k)\in L}q_{t,j,k}^{line}\right)^2}\leqslant c_i^{trans}+c_i^{slack},\forall i,t \tag{24}$$

where c_i^{trans} represents the transformer capacity in subarea i. In sum, hourly optimal power flow model optimizes the slow charging power of home-based EVs and set-points of SOPs to minimize the operation cost and transformer overload. Once the model is solved, we are able to obtain the charging profiles and examine the overload situation. In addition, we can also determine the planning of rooftop PV given C_{add}^{PV}.

Solution for co-evolution of urban power networks and electric mobility

To address the above mentioned UPNs spatial imbalance and transformers overload challenges, we proposed an effective solution towards co-evolution of urban power networks with and electric mobility by coordinating the EV smart charging, the planning of the rooftop PV and SOPs. Based on the above-mentioned rooftop PV potential estimation and EVs charging loads characteristics, we have formulated an hourly optimal power flow model of UPNs considering the transformers overloading and SOPs operation in the previous section. Once solved, we can determine the capacities and location of rooftop PV and SOP installation in different scenarios year by year. Figure 4 organizes each step of the planning model.

The planning starts at 2026. First, EVs charging characteristics are simulated, and then the optimal power flow model is solved to check whether transformers overload happens. If transformers overload happens, the SOPs installation in the corresponding area will be implemented. The other terminal of SOPs is chosen to connect the neighbor subarea with the lowest transformer load ratio. The capacity of SOPs increases in an iterative manner till transformer overload is eliminated.

RESULTS

GPS trajectories of urban mobility

Figure 5 shows the simulated results of charging demands of 50,000 work-related EVs. It can be observed that different quarters of Xi'an city have spatially unbalanced charging loads. In specific, the charging demands in the southwest quarter are nearly 3 times higher than those in the southeast, which causes the different operation statuses of corresponding transformers.

Deep learning-based estimation of rooftop PV potential

Figure 6A illustrates that the pixel-level accuracy rate of the validation dataset is 92.3%, which demonstrates the effectiveness of the deep learning-based methods. Results indicate that the rooftop area in Xi'an urban areas reach 11.21km^2. In addition, the spatial distribution of the rooftop area is not uniform among 16 subareas, as shown in Figure 6B.

Identifying potential bottlenecks of urban power networks

We utilize the hourly optimal power flow simulation of UPNs in Xi'an city to quantify the potential bottlenecks in the next 10 years from 2026 to 2035. The electricity loads for all transformers are captured with average 14.79% increase per year. Firstly, we calculate the maximum transformers loading of all 16 subareas in a typical day from 2026 to 2035. As shown in Figure 7A, the earliest bottlenecks for over the transformers' capacity limits of the UPNs emerge in 2026 due to the boost of urban electric mobility and associated EVs charging loads. Till 2032, all subareas in Xi'an will suffer from the severe transformers overloading, which impairs the normal operation of UPNs.

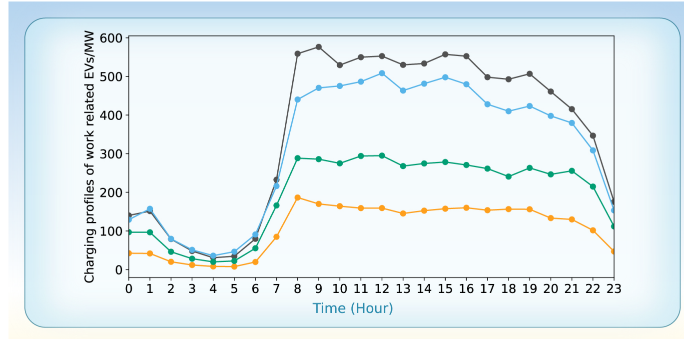

Figure 5. Results of Monte Carlo simulation for charging demands.

We then investigate the spatial distribution of transformers' capacity shortage in Xi'an from 2031 as it is exactly the year before the earliest bottlenecks emerging time. As shown in Figure 7B, the largest shortage of transformers capacities will be experienced in northwest UPN of Xi'an, of which the capacity shortage will increase from 6.27% in 2026 to 287.90% in 2035. Compared with simulation results of EVs charging demands in Figure 5, it is clear that the urban electric mobility aggravates the spatial imbalance of UPNs and overload of transformers, which will be a serious bottleneck for the future operation of UPNs. As will be discussed later, soft open points (SOPs) are applied to alleviating the spatial imbalance of UPNs efficiently.

We take a closer look at the transformer overloading probabilities in a typical day in 2035, as shown in Figure 7C. We found that overloading generally happens between 8 am to 10 pm, which is mainly caused by the un-schedulable work-related EVs charging demands (Figure 7C). Hence, we address the related bottlenecks via increasing the rooftop PV capacities in the next section. In addition, 87.5% of the overloading is brought about by the home-based EVs charging demands ranging from 6pm to 10pm. As will be indicated later, the EVs smart charging could be the effective solution to the challenge.

Solution for co-evolution of urban power networks and electric mobility

To address the above mentioned UPNs spatial imbalance and transformers overload challenges, we proposed an effective solution towards co-evolution of urban power networks with and electric mobility by coordinating the EV smart charging, the planning of the rooftop PV and SOPs. As shown in Figure 8A, the EV smart charging implemented from 2026 could effectively shift the peak charging demands from the evening peak period to overnight. Without EVs smart charging, the 16 subareas' total charging demands peak will occur at 7 pm with a maximal value of 2165.55 MW, which significantly aggravate the transformer overloading problem. In contrast, with EVs smart charging, the highest peak demands are reduced by 74.6% from 2165.55 MW at 7 pm to 549.44MW at 3 am. The charging demands are shifted to the 1 am to 6 am period, which leads to a smooth transformer loading for the whole day. After 2031, however, the EV smart charging alone cannot fully eliminate the transformer overloading bottleneck, which is shown in Supplementary.

In 2032, the rooftop PV will be implemented to provide extra renewable power to the work-related EVs induced charging loads during daytime. As shown in Figure8B & C, bottlenecks of the subarea 3 can initially be covered by the installed rooftop PV, of which the capacity amounts to 258.16MW in 2032 and 516.33MW in 2035. Still in 2032, the SOPs needs to be installed to alleviate the spatially load imbalance for different areas of Xi'an. Specially, SOPs will connect multiple subarea pairs in 2035 with a total capacity of SOPs up to 345 MVA. Overall, as shown in Figure 8D, by a UPNs and electric mobility co-evolution solution coupling EV smart charging with rooftop PV and SOPs implementation, the potential bottlenecks of UPNs in Xi'an is able to be fully eliminated without the large-scale upgrade such as the building of new feeders or substations. The maximum transformer loading is able to be

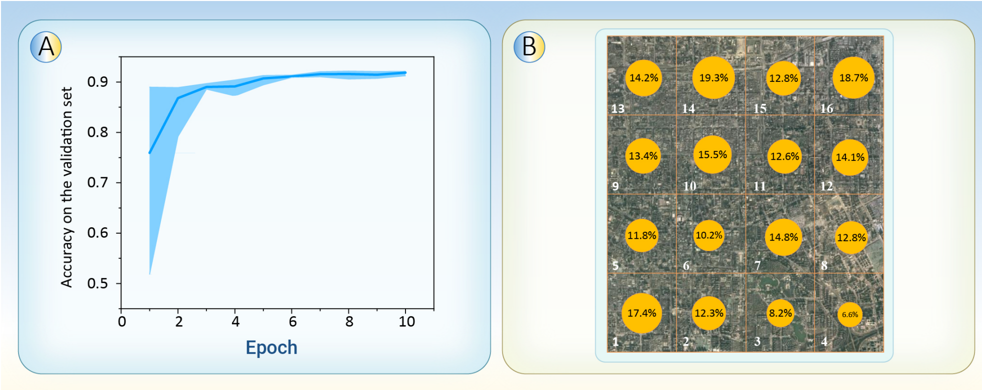

Figure 6. Results of rooftop PV potential analysis.

controlled within the limits accordingly, which enables the achievement of China's EVs integration goal.

DISCUSSION

Urban power networks (UPNs) are the backbone to facilitate the EVs integration and further support the urban decarbonization. However, severe challenges appear for the UPNs considering the ambitious target of electrifying transport sector. Accordingly, two vital questions remain unsolved: Are the UPNs ready? If not, what is imperative to do?

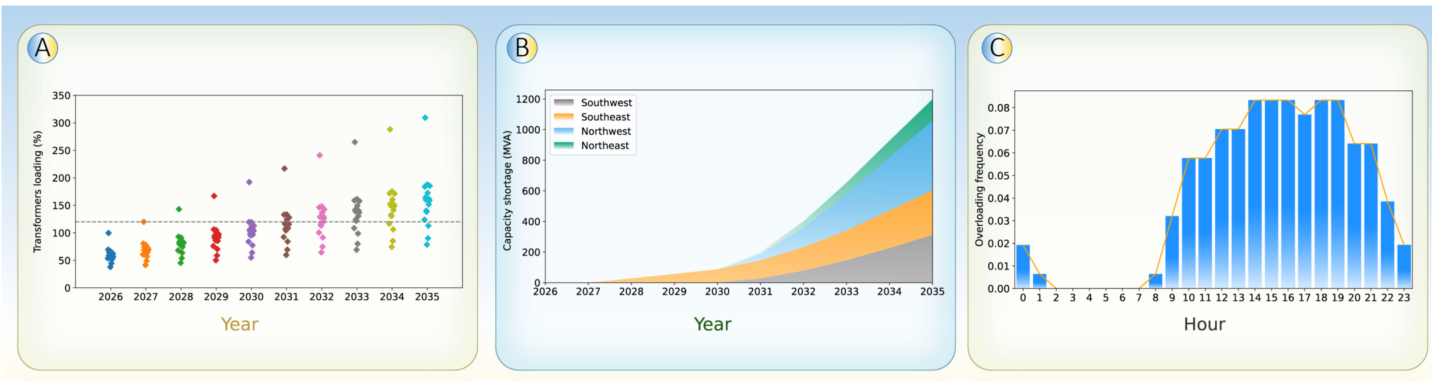

Figure 7. Bottlenecks of city power networks with urban electric mobility.

In this study, we firstly propose a data-driven approach to simulate temporal and spatial EVs charging demands based on GPS trajectories data for identifying and quantifying the potential bottlenecks of UPNs. Then we further propose an effective solution to enable the sustainable co-evolution of UPNs and electric mobility. We take Xi'an city as an example and found that even without large-scale upgrade, UPNs in Xi'an are able to support the achievement of China's EVs integration target if the following measures are implemented: (i) employing the EVs smart charging to shift the evening charging demand peak to the overnight period, (ii) developing distributed rooftop PV to energize the city with low-carbon electricity, and (iii) enhancing the flexibility of UPNs operation by deploying SOPs could efficiently address the problems of transformer overload and the demand spatial imbalance.

Our study, consistent with the previous research, indicates that the temporal peak of EVs charging demands will impair the UPNs operation. Thus, it is necessary to implement the EVs smart charging. On top of that, we take a step further and found that electrification of transport sector will also bring about the spatial imbalance of EVs charging demands. To address the gap in the existing literature, we bring together two different data sources of satellite images and historical drivers' GPS trajectories in Xi'an city. The spatial differences in rooftop PV potential and EVs charging choices are carefully evaluated, which are neglected in the related work. Moreover, we extend the proposed solution via including the planning of SOPs for alleviating EVs integration impacts on the different subareas of UPNs in Xi'an.

It is also necessary to consider other factors of EVs integration such as different uses of EVs.[90] EVs with different uses take different charging choices (fast or slow charging) and times, which have profound influence on the EVs charging demands. Our analysis indicates that work-related EVs with the fast charging lead to transformer overloading problem during daytime and developing rooftop PV could mitigate the problem; whereas the home-based EVs with the slow charging is schedulable by implementing EVs smart charging to avoid the undesired peak load. However, one limitation in this analysis is the historical drivers' GPS trajectories are based on the ride-hailing order service dataset. The utilized dataset is equivalent to the sampling from the whole set of vehicles' trajectories, which could represent the majority but not the entire traffic distribution. The simulation of EVs charging characteristics could be more accurate if more vehicles trajectory data are accessible, which is possible with the fast development of smart transportation systems.

Our work foresees the emerging challenge led by transport sector electrification and proposes a sustainable solution by co-evolution of UPNs and electric mobility. Based on our work, future studies could further investigate the optimal siting issue of charging facilities based on the spatial distribution of EVs charging demands, evaluate the effectiveness of battery storage devices to support EVs integration, and design incentive-based policies to better reduce the peak of EVs charging demands, to name a few.

In addition, the applicability of the proposed approach extends beyond the co-evolution of UPNs and electric mobility. While our study focused on addressing the challenges posed by transport sector electrification, it is essential to recognize that the same data-driven methodology and solution could be adapted to tackle other critical decarbonization challenges, such as decarbonization of heat and industry. By leveraging similar data sources, including satellite images and GPS trajectories, it becomes possible to identify and quantify the bottlenecks in these sectors and devise effective solutions to promote the sustainable integration of renewable energy sources and novel power electronic devises. Future research endeavors could explore the application of our approach in diverse energy domains, paving the way for comprehensive and harmonious co-evolution strategies in various aspects of the urban energy landscape. As a piece of future work, this expansion of our approach holds significant promise in advancing the transition towards a low-carbon and resilient urban energy infrastructure, thereby contributing to the overarching goal of achieving carbon neutrality and sustainable development.

CONCLUSION

The rapid electrification of urban mobility poses significant challenges to UPNs, including transformer overloads and spatial load imbalances. This study presents a data-driven co-evolution framework that synergistically integrates EV smart charging, rooftop PV, and SOPs to enable sustainable UPN development without large-scale grid upgrades. Using Xi'an, China, as a case study, we show that unmanaged EV adoption would cause transformer overloads as early as 2032. However, smart charging can shift up to 74.6% of evening peak demand to off-peak hours. Rooftop PV provides local renew-

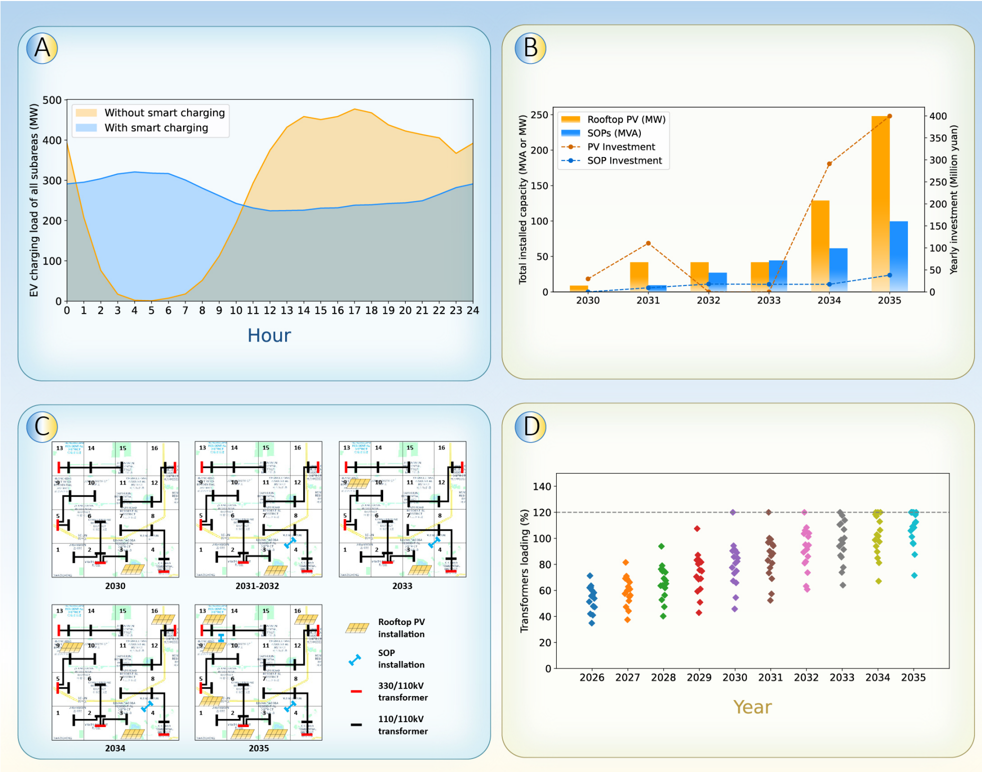

Figure 8. The results of coevolution of city power networks and urban electric mobility.

able energy to meet daytime charging needs, while SOPs mitigate spatial imbalances by transferring power between subareas. Together, these strategies successfully eliminate projected bottlenecks and ensure that existing UPNs can support China's national EV integration targets. This approach offers a scalable, upgrade-minimizing pathway for cities worldwide to achieve low-carbon mobility and resilient power infrastructure simultaneously.

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AUTHOR CONTRIBUTIONS

T. Q. designed the study and performed the research. M. F., R. J., Z. W., W. M. and Y. Z. contributed to data processing and manuscript drafting. C. S. and J. W. contributed to the study design and research methodology. Q. H., X. W, Z. W, and X. W. provided administrative support. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Data are available from the corresponding author upon reasonable request.