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Unraveling the effect of electricity price on electric vehicle charging behavior: A case study in Shenzhen, China

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ABSTRACT

Estimating price elasticity of demand for electric vehicle charging contributes to the accurate determination of charging price, thereby improving electric vehicle adoption and energy sustainability. However, few studies have studied the impact of electricity price on electric vehicle charging behavior, especially the demand spillover effect caused by price fluctuations. To fill the gaps, on a citywide dataset of public charging piles in Shenzhen, China, first, correlation coefficients and hypothesis tests are used to determine the relationship between charging demand and price. A learning model incorporating two-layer graph attention, temporal pattern attention, and knowledge-embedded meta-learning is developed for accurate spatio-temporal regression. Impulse response analysis is conducted to unravel several noteworthy phenomena: (1) public charging demand is inelastic to electricity price, with an average elasticity of −0.76, and distinction between different functional areas and times is revealed; (2) negative price impulses marginally change the elasticity, while positive ones make electric vehicle charging users more price sensitive, and (3) the spillover effects caused by price increases and decreases bring 89.48% and 53.88% of its local demand changes to neighbors, respectively, with a scope of 3.45 kilometer. These findings provide policy implications for promoting electric vehicle charging to facilitate renewable energy transition.

1. Introduction

Governments have set up policies to promote electric vehicles (EVs) in their transportation sector in recent years, with the motivation of reducing fossil fuel dependency, mitigating air pollution and global warming, and facilitating the achievement of United Nation's Sustainable Development Goals on carbon neutrality (IEA, 2021; Isik et al., 2021; Wu & Lin, 2021). In this context, considerable uptake of electric vehicles has already begun in specific cities worldwide, and the global electric vehicle ownership is expected to increase to 140 million by 2030 (Heidrich et al., 2022). Despite the many benefits of vehicle electrification, this proliferation poses significant challenges to the reliability and resilience of urban power grids and transportation systems (Borlaug et al., 2023). Considering the continuous supplement of EV charging spaces is unsustainable to tackle the challenges, recent studies have proposed to develop smart pricing strategies for EV charging in urban areas, e.g., dynamic pricing and co-pricing (Cedillo et al., 2022; Valogianni et al., 2020; Zhang et al., 2019; Zhao & Lee, 2022). As the foundation to achieve such an optimization, understanding the adaptive changes in EV charging behaviors in response to electricity price adjustments has attracted increasing attentions to facilitate vehicle electrification and rethink green mobility (Palaniyappan et al., 2024; Yang, Cui et al., 2024).

Research on EV charging infrastructure and the relevant economics has been carried out globally. A number of early studies have demonstrated that charging price is one of the major consideration when users select charging stations (Hu et al., 2016; Li & Ouyang, 2011). The specific impact of price on energy utilization has also been studied for many years. A study by China's National Development and Reform Commission (NDRC) notes that in Shanghai, 75% of EV users choose to charge in off-peak hours when peak-time price are twice as high as off-peak hour price (Jian et al., 2018). Price elasticity of demand is mostly used in economic studies to quantify how the quantity of demand varies in response to changes in the price of a good. For

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calculations, price elasticity of demand is equal to the percentage change in demand divided by the percentage change in price. Previous research demonstrates that residential energy consumption has a low price elasticity of demand, including EV charging. A study shows that the global price elasticity of demand for residential electricity is about −0.45 (Zhu et al., 2018). EV charging is strongly inelastic (i.e., the price elasticity of demand is approximately 0) at night when electricity prices are low in the San Diego Gas & Electric service areas (Cook et al., 2014). A recent study notes that in microgrids, residential electricity is typically very inelastic, at about −0.2; commercial and industrial electricity are also inelastic, at about −0.3 and −0.54, respectively, which is relatively more elastic than residential electricity (Datta & Das, 2023). Current research mostly focuses on the price impacts for large-scale multi-industry, and there is still a lack of research on price-demand relationships for citywide EV charging. Studies of different times and different urban areas are also lacking. Moreover, increasingly progressive information distribution systems and well-developed road networks have made it possible for demand in one region to be influenced by demand and prices in neighboring regions. Current research focuses only on local and ignores spatial spillover effects on the one hand, and does not distinguish between different times and different regions on the other. This leads to the economic grounds and impact of some EV charging price policies are unclear (Kuang et al., 2024; Li et al., 2023).

To quantify price impacts, it is a common practice to build regression models that simulate the relationship between variables and estimate their price elasticity of demand through impulse response analyses accordingly, which measures the responsiveness of the demand of service to changes in its price (Hössinger et al., 2017; Lee et al., 2020; Skare et al., 2021). Early studies used linear functions to model the relationship between price and demand (Inoue & Kilian, 2013). In the last few years, plenty of studies have proposed to take advantage of machine learning techniques to model the nonlinear relationships between variables (Deng et al., 2022; Ge et al., 2020; Palaniyappan et al., 2024; Ullah et al., 2022; Yi et al., 2020). These studies provided insights into the regional demand-side management for smart charging of EV. Nevertheless, their main focus remains on the local situations, ignoring the corresponding demand change in surrounding areas. As regions in cities are now closely linked, the magnitude and scope of the spillover effect of EV charging demand between adjacent areas caused by price changes need to be considered and quantified, in order to avoid unexpected congestion of EV charging in neighboring areas when adjusting pricing schemes. With the development of data collection and storage technologies and the enhancement of computer calculating power, data-driven and neural networks are nowadays widely used to capture the complex relationships behind the EV charging demand and prices (Almutairi & Aljohani, 2024; Yang, Liu et al., 2024). However, there is still a lack of research that combines the excellent modeling capabilities of neural networks with impulse response analysis to quantitatively unravel how EV charging demand is affected by price.

To fill the research gap above and investigate the price impact on EV charging behavior, first, two correlation coefficients (i.e., Pearson Correlation Coefficient (Karl, 1895) and Spearman Correlation Coefficient (Schober et al., 2018)) and three hypothesis tests (i.e., F test, chi-square test, and likelihood ratio test (Dumitrescu & Hurlin, 2012)) are used to determine the relationship between two time-series features, i.e., EV charging occupancy and price. Second, a newly proposed multivariate deep learning model is developed to learn spatio-temporal patterns, which take advantage of advanced spatial attention mechanism and temporal pattern attention mechanism (Qu et al., 2024; Shih et al., 2019; Velickovic et al., 2018). Third, experiments based on a data analysis tool Impulse Response Function (IRF) (Inoue & Kilian, 2013) are designed to investigate the temporal and spatial impacts of price on EV charging behavior.

In this paper, a quantitative analysis is conducted based on a real-world dataset of 18,061 public EV charging piles in a first-tier city Shenzhen, China, from June 19 to July 18, 2022. In particular, the main contributions of this paper are as follows:

- The price elasticity of demand for public EV charging in Shenzhen is estimated. The average price elasticity of demand for public EV charging is estimated to be −0.7581, which suggests that EV charging in the studied city is inelastic. Since the studied city is one of the global leaders in vehicle electrification, the estimates can be instructive for EV charging pricing and infrastructure planning in other cities.
- Several noteworthy differences and consistency between weekdays and weekends, daytime and nighttime, Central Business District (CBD) and other regions are uncovered and deciphered respectively. The study finds that charging demand in the CBD is more inelastic than in other areas, at −0.7236 and −0.7654, respectively, and this is significantly observed during weekday nights and most of the rest days. Besides, it can be found that users are price-sensitive during moderate-intensity regional charging needs and relatively insensitive during low- or high-intensity regional charging needs.
- This study disentangles how regional price adjustments influence the EV charging demand in their vicinity, both in terms of magnitude and scope. The magnitudes of demand spillover induced by positive and negative price impulses are 89.48% and 53.88%, respectively, while the radius of spillover is estimated to be 3.45 km.

The remainder of this paper is structured as follows. Section 2 first describes the development background of electric vehicles and charging services globally and in the studied city, then provides a literature review that presents some researches relevant to the topic. In Section 3, the applied regression model and analysis methods are introduced. Then, Section 4 describes the EV charging dataset and specific experimental setup. Then, Section 5 provides detailed results and discussions of our analysis. Further policy discussions, conclusions, and future works are drawn in Section 6.

2. Background and literature review

Countries and regions around the world vigorously promote vehicle electrification to facilitate green energy utilization and reduce environmental pollution, with financial incentives being one of the most important means (Martins et al., 2023; Mersky et al., 2016). In China, in addition to EV production, plates and taxes, the government provides substantial economic subsidies for electric vehicle charging services, and the economic cost of energy to drive an electric vehicle is about 1/5 that of a gasoline vehicle (Yang et al., 2020). In Europe, the cost of charging at public charging stations is also attractive compared to the cost of gasoline (Lanz et al., 2022). Developed countries and regions lead the development of vehicle electrification, and one of the reasons for this is their easy access to electricity and the proliferation of electric vehicle charging piles (Abotalebi et al., 2019). However, while charging services are growing rapidly, charging service providers are struggling to make satisfactory profits, and it is unsustainable for the government to heavily subsidize the operation of charging piles (Kim et al., 2022; Zhang, Song et al., 2018). Over the past five years, Chinese government has progressively reduced subsidies for the construction and servicing of charging piles, instead requiring enhanced charging network coverage and promoting residential charging infrastructure (The State Council of PRC, 2023). The price of public electric vehicles charging in China consists of two parts: electricity fee and charging service fee. The electricity fee is charged in accordance with the local electricity pricing policy; the charging service fee is mainly used to recover the investment in charging infrastructure and the operating costs. Note that in this study, electricity fee and charging service fee are no longer distinguished, i.e., all prices mentioned in this article are the sum of electricity fee and charging service fee, which is equal to the users' cost. Currently, charging services in China are priced by companies on a market-based basis. The highest-priced services, such as Tesla

Table 1
Representative estimates of price elasticity of demand.

Energy	User	Elasticity	Model	Scope	Location	Reference
Gasoline	Vehicles	−0.40	Non-linear	National	Canada	Rivers and Schaufele (2017)
Gasoline	Different vehicles	[−0.35, −0.08]	Linear	Hanshin Expressway	Japan	Ahmed et al. (2023)
Gasoline	All	[−2, −0.5]	Linear	Urban	Azerbaijan	Mikayilov et al. (2020)
Natural Gas	Industry	−0.85	Linear	National	China	Zhang, Ji et al. (2018)
Electricity	Households	−0.45	Machine learning	Global	–	Zhu et al. (2018)
Electricity	Households	−0.43	Linear	National	Germany	Schulte and Heindl (2017)
Electricity	Industry	−1.20	Linear	National	US	Burke and Abayasekara (2018)
Electricity	Economy	−0.29	Linear	National	South Africa	Masike and Vermeulen (2022)
Electricity	Vehicles	[−1.5, −0.2]	Machine learning	Urban	Beijing	Bao et al. (2021)
Electricity	Vehicles	−0.76	DNNs	Urban	Shenzhen	Ours

Supercharging, can be as high as 2.59 CNY/kWh; the lowest-priced services are settled with residential electricity at about 0.3 CNY/kWh. Exploring the impact of charging prices on charging demand have been a hot research topic, but city-wide quantitative studies are still lacking, which leaves businesses still ungrounded in setting prices, especially when differentiated pricing is required (Bao et al., 2021; Cook et al., 2014; Jian et al., 2018).

Shenzhen is a first-tier city in the south of China with a high level of economic development and a warm climate suitable for electric vehicles. The Shenzhen government restricts vehicles on the road by restricting license plates, but with the current policy new energy vehicles (including electric vehicles and plug-in hybrids) are not restricted, meanwhile their purchase tax is not charged. Currently, almost all buses and cabs in Shenzhen are electric vehicles. By 2025, the proportion of new energy vehicles among newly registered vehicles will reach 60%, and the total number of new energy vehicles in the city will reach about one million. This has created a huge demand for electric vehicle charging. The Shenzhen Development and Reform Commission expects around 43,000 fast charging piles and 790,000 slow charging piles will be built (Shenzhen Development and Reform Commission, 2021).

In order to explore short-term economic effects, it is common practice in many fields to build multivariate regression models and estimate the corresponding price-demand relationship through impulse response analysis. In Table 1, several representative estimates of energy consumption elasticities are summarized. For example, the price elasticity of demand for gasoline vehicle in Canada is estimated by a double logit model to approximately −0.40 (Rivers & Schaufele, 2017) ; an autoregressive distributional lag model is constructed to estimate the elasticity of demand for natural gas across industries in China to be about −0.85 (Zhang, Ji et al., 2018) and the price elasticity of gasoline demand is estimated from −0.5 to −2 in Azerbaijan, by employing vector auto-regression models (Mikayilov et al., 2020). There have also been a number of studies quantitatively exploring the price elasticity of demand for electricity in different sectors, including residential, industrial and commercial electricity consumption (Burke & Abayasekara, 2018; Datta & Das, 2023; Masike & Vermeulen, 2022; Schulte & Heindl, 2017; Zhu et al., 2018). However, these studies have been conducted for a wide range of electricity sectors. Limited studies have provided estimates of the price elasticity for public EV charging in urban areas (Bao et al., 2021), which is an essential econometric indicator for the development of vehicle electrification in a city. Besides, previous studies focus mainly on local economic effects and pay little attention to how demand and price changes in one area affect neighboring areas. Moreover, due to the limitation of linearity assumptions, previous studies remained challenges in uncovering the non-linear pattern of price-induced effects that varies across time and space.

Machine learning and deep learning provide promising ideas for modeling nonlinear relationships between multi-source data and have become a hot research topic. Many studies utilize neural networks and deep learning to construct highly accurate charging demand regression model, some of which consider price as an auxiliary factor (Wang et al., 2023). Our previous work proposes mixed pseudo-sample meta-learning based EV charging demand prediction model with effective learning of price-demand adaptive changes (Qu et al., 2024). Moreover, physics-informed neural network is employed to model the relationship between demand and price and achieve accurate spatio-temporal prediction (Kuang et al., 2024). As a recent illustration, the influence of several significant factors (i.e., state of charge, season, lighting condition, and time of the day) on EV charging choice is estimated using an interpretable learning framework (Ullah et al., 2023). A study employs a multi-input nonlinear autoregressive neural network for 24-hour-ahead EV charging market price prediction (Gharibi et al., 2023). Besides, dynamic pricing strategies aiming at maximizing revenue or utilization for charging stations have been explored through deep learning or reinforcement learning methods (Zhao & Lee, 2022). Deep learning approaches, including graph neural networks and convolutional neural networks, allow for modeling the spatial spillover effects of charging demand under price impact. However, there is still a lack of research on combining deep learning models with excellent performance and impulse response analysis.

In summary, electric vehicles are favored for their low cost and environmental friendliness. However, governments are still investing huge subsidies to promote electric vehicles and charging services. Although many studies have been conducted to quantify the price-driven impacts for different energy, citywide EV charging is still a understudied emerging direction. Previous research methods have been criticized on two aspects, namely their linear assumptions and the lack of research on spatial effects. Nowadays, deep learning and neural networks provide promising methods to enable modeling spatio-temporal multivariate nonlinear relationships. But quantitative methods and relevant insights remain to be explored to fill the research gap.

3. Methods

A hierarchal spatio-temporal analytic framework is proposed, as shown in Fig. 1, consisting of three procedures, namely **Step 1**. correlation tests, where two coefficients (i.e., Pearson (Karl, 1895) and Spearman (Schober et al., 2018)) and the Granger Causality Test (GCT) (Dumitrescu & Hurlin, 2012) are used to identify the correlation relationship between EV charging demand and prices; **Step 2**. near-future EV charging occupancy prediction, in which a deep learning model combining graph neural networks and temporal pattern attention is developed to capture not only temporal features of data, but also the spillover effects; **Step 3**. impulse response analysis, where the impacts of electricity price on EV charging behavior are quantified. In the following subsections, the details of each part will be described.

3.1. Correlation tests

Two correlation coefficients and three hypothesis tests are used to determine the relationship between two time-series features, i.e., EV charging occupancy and price, for each traffic zone with a time-based pricing scheme. The correlation coefficients are the Pearson Correlation Coefficient (PCC) (Karl, 1895) and the Spearman Correlation Coefficient (SCC) (Schober et al., 2018), which describe the strength and direction of the linear significance between two tested variables. The

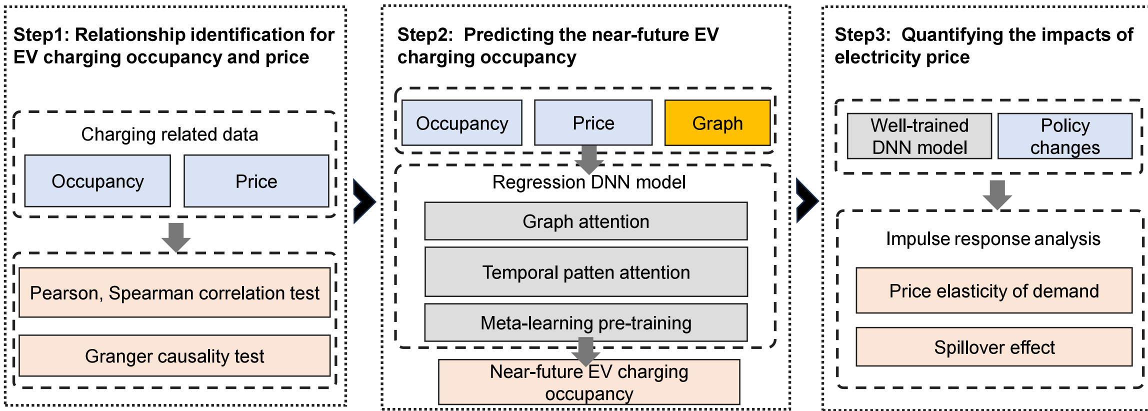

Fig. 1. Overview of the methods used in this study.

hypothesis tests are the F test, chi-square test, and likelihood ratio test, which belong to the Granger Causality Test (GCT) (Dumitrescu & Hurlin, 2012).

Based on the two coefficients, the following steps are executed to complete the correlation test for a specific traffic zone. First, the minimum absolute value of the two coefficients is calculated, which denoted by R. Then, two thresholds of 0.2 and 0.5 are defined. If a zone's R is greater than 0.2 at or above 99% confidence level, it passes the correlation test. And if R is greater than 0.5 at or above 99% confidence level, it can be concluded that the correlation of EV charging occupancy and price is strongly significant.

The GCT is used to check whether the prices Granger-cause the charging occupancy in a specific traffic zone. The maximum lag of one hour is configured for prices, since the impact of price fluctuations on the demand would occur within 60 min is assumed. As the data is sampled at 5-min intervals, the smallest p-value among the 12 lags is used for each hypothesis test. The following steps are executed to complete the causality test. First, different from the correlation test, the maximum p-value of the three hypothesis tests is calculated, which is denoted by p. Then, a threshold of 0.05 is defined, indicating a 95% confidence. At last, if a zone's p is smaller than the threshold, it passes the causality test. In other words, it can be assumed that there exists a Granger-cause among EV charging occupancy and price.

Both the correlation and causality tests can convincingly demonstrate the relationship between EV charging price and occupancy from their side. Therefore, it can be concluded that if one of the tests is passed, charging price is an influencing factor of the demand.

3.2. Spatio-temporal regression model

The applied spatio-temporal regression model consists of three modules, as shown in Fig. 2, namely a graph embedding module, a multivariate temporal decoder module, and a model pre-training module. Demand (i.e., occupancy) and price data are used as feature inputs. First, a cross-feature 2D convolution is used to fuse the two features to obtain high-dimensional features. After that, a two-layer multi-head graph attention mechanism (GAT) is used to learn multi-hop spatial heterogeneous characteristics. The local, 1-hop, and 2-hop feature matrices are taken out, fused through a network similar to the residual connection, and then stacked. Long and short-term memory (LSTM) is used to extract features in temporal dimension, and the resulting high-dimensional hidden states are fed into a multivariate decoder consisting of temporal pattern attention and a multilayer perceptron. Temporal pattern attention contains convolutional neural network and temporal-feature attention mechanism, which effectively improves the multi-dimensional feature extraction capability. Moreover, knowledge-embedded meta-learning has been innovatively proposed in order to accurately capture the demand-price variation patterns and prevent model overfitting. In this module, the model can be informed of some prior knowledge (e.g. how much the demand of the commodity would normally fall as a result of a price increase). Pseudo-samples are generated based on prior knowledge and mixed with real samples. During first-order model-agnostic meta-learning (FOMAML) training, the pseudo-samples are progressively reduced and the model gradually converges to the pattern of real data.

Given a well-trained deep learning model $\mathbf{F}$, the regression function can be formulated as Eq. (1), where $\mathbf{o}$ and $\mathbf{c}$ are the historical occupancy and prices; $\mathbf{o}^t$ denotes the vector of EV charging pile occupancy in all studied traffic zones at time t; f and w represent the forecasting and backtracking time intervals, respectively; $\mathbf{y}$ is set to be the predicted near-future EV charging occupancy, i.e., $\mathbf{o}^{t+f}$.

$$\mathbf{y} = \mathbf{o}^{t+f} = \mathbf{F}(\mathbf{o}^t, \dots, \mathbf{o}^{t-w}, \mathbf{c}^t, \dots, \mathbf{c}^{t-w}) = \mathbf{F}(\mathbf{o}, \mathbf{c}) \tag{1}$$

3.3. Impulse response analysis

In this subsection, an experiment is designed based on a widely-used statistical tool, Impulse Response Function (IRF) (Inoue & Kilian, 2013). The IRF includes two procedures: first, add a specific impulse into the regression model; second, measure the corresponding predicted changes, i.e., model response. Given a price impulse in a specific traffic zone i, the calculation of its IRF can be formulated as Eq. (2).

$$\Delta\mathbf{y}_i = \mathbf{F}(\mathbf{o}, \mathbf{c} + \Delta c_i) - \mathbf{F}(\mathbf{o}, \mathbf{c}) \tag{2}$$

where Δ refers to the difference between the post-pulse and pre-pulse values, the same below; $\mathbf{F}$ represents the regression model; $\mathbf{o}$ and $\mathbf{c}$ denote the occupancy and prices for all the traffic zones during the backtracking period; Δc_i denotes the price impulse in zone i, which equals the standard deviation of price fluctuations in the training set; and $\Delta\mathbf{y}_i$ is the change of EV charging occupancy in response to Δc_i.

Based on impulse-response pairs, the following steps are executed to quantify the underlying patterns and summarize them into a genetic law, i.e., calculate the price elasticity of demand and estimate the spillover effect between adjacent zones. First, the price elasticity of EV charging demand ξ_i for a specific traffic zone i can be calculated by Eq. (3) using the point elasticity method (Zhu et al., 2018).

$$\xi_i = \frac{\Delta y_i / y_i}{\Delta c_i / c_i} \tag{3}$$

where c_i and y_i are the average EV charging price and occupancy for zone i during the studied period; Δc_i and Δy_i denote the average price impulse and corresponding response for zone i during the studied period. There are two thresholds that distinguish the meaning of the metric, i.e., 0 and 1. If $\xi_i < 0$, it indicates that the price has a dampening effect on the demand and vice versa, a facilitating effect. $|\xi_i| < 1$, $|\xi_i| = 1$, and $|\xi_i| > 1$ indicate an inelastic, unitary, elastic demand, respectively, which mean that a given percentage change in price will

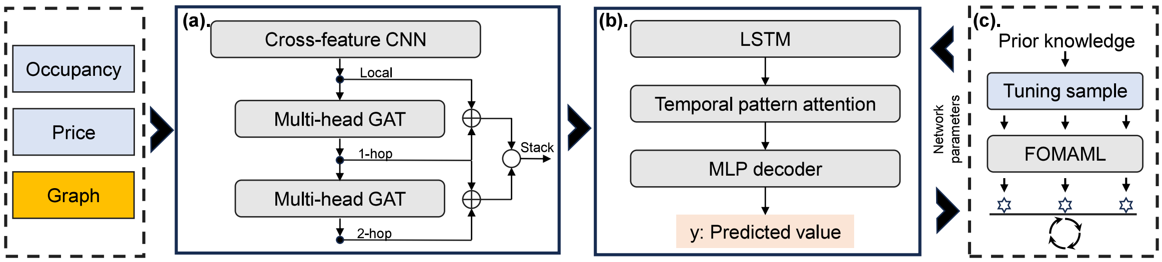

Fig. 2. The structure of the applied deep learning model, which consists of (a). Graph embedding module, (b). Multivariate temporal decoder module, and (c). Model pre-training module.

cause a smaller, equal, and greater percentage change in quantity demanded, respectively. In general, the smaller the absolute value, the less price sensitive the demand is. In addition to calculating the total elasticity in Shenzhen, differences in elasticity belonging to different time periods or different functional areas will be distinguished, such as, daytime and nighttime, weekdays and weekends, CBD and other regions.

The second part of the IRF is a discussion of the occupancy changes in 1-hop and 2-hop neighbors. Specifically, such a spillover effect is quantified from two aspects, i.e., magnitude and scope. The magnitude measures how much local demand spills over into its neighbors, and the scope indicates how far the effects of price fluctuations spread. Within that distance, areas can be assumed with confidence to be affected by the spillover effect. Given J 1-hop and K 2-hop neighborhoods surrounding a studied traffic zone i, the magnitude of demand spillover can be calculated by Eq. (4).

$$\begin{aligned} \eta' &= \frac{\sum_{j=1}^{J} \Delta y_j / y_j}{\Delta y_i / y_i}, \\ \eta'' &= \frac{\sum_{k=1}^{K} \Delta y_k / y_k}{\Delta y_i / y_i} \end{aligned} \tag{4}$$

where η' and η'' indicate the ratios of demand changes in 1-hop and 2-hop neighbors, respectively, relative to the change in an impulsed zone i; y_j and y_k represent the observed occupancy in surrounding zones j and k, respectively; Δy_j and Δy_k are the corresponding responses in the surrounding zones j and k, respectively; $j \in \mathcal{N}_J, k \in \mathcal{N}_K$, while $\mathcal{N}_J$ and $\mathcal{N}_K$ are the sets of 1-hop and 2-hop neighbors. Based on the same assumptions, the cross price elasticity of demand for neighboring EV charging can be calculated by multiplying the local price elasticity ξ_i and η' or η'', as presented in Eq. (5).

$$\begin{aligned} \xi_i' &= \frac{\sum_{j=1}^{J} \Delta y_j / y_j}{\Delta c_i / c_i} = \xi_i \cdot \eta', \\ \xi_i'' &= \frac{\sum_{k=1}^{K} \Delta y_k / y_k}{\Delta c_i / c_i} = \xi_i \cdot \eta'' \end{aligned} \tag{5}$$

where ξ_i' and ξ_i'' are the cross price elasticity of demand for 1-hop and 2-hop neighbors' public EV charging, respectively, representing the percentage change in total demand in the neighboring zones $j \in \mathcal{N}_J$ and $k \in \mathcal{N}_K$, when the charging price in the impulsed zone i changes.

Given the cross price elasticity and the distances between studied zones, the scope of demand spillover can be measured by statistical analysis. A discriminator to determine the average spillover radius is defined, i.e., a maximum distance in which 95% of the transportation districts have a cross-price elasticity greater than 0.1. According to this, it can be assumed with 95% confidence that if the distance between a traffic zone and the price-fluctuating zone is less than r, the zone's public EV charging load will be affected by the price change from the price-fluctuating zone. As a result, the distance can be considered as the scope of the spillover effect.

4. Data and experimental setup

The data used in this study is drawn from a publicly available mobile application, which provides the real-time availability of charging piles (i.e., idle or not). Within Shenzhen, China, a total of 18,061 charging piles are covered during the studied period from 19 June to 18 July 2022 (30 days). Note that the EV charging behavior is denoted by the number of in-use piles in a given traffic zone, i.e., pile occupancy in this study. Then, the data are organized as a set of regional pile occupancies and prices updated every five minutes based on the traffic zones delineated by the sixth Residential Travel Survey of Shenzhen (Zhou & Ma, 2021). As shown in Fig. 3, there are 247 traffic zones with charging data, 57 of which use a time-of-use (TOU) pricing scheme for EV charging, while the rest use a fixed pricing scheme. The Central Business District (CBD), with 62 studied traffic zones, is singled out to investigate the discrepancy in different urban functional areas (Zhang & Gao, 2023). From a spatial perspective, all the studied traffic zones are connected with their adjacent neighborhoods to form a graph-based traffic network with 247 nodes and 1006 edges. From a temporal perspective, there are 8640 ($12 \times 24 \times 30$) timestamps during the studied period. The dataset is divided into training, validation, and test sets in a 6:2:2 ratio in chronological order, i.e., Day 1–18, Day 19–24, and Day 25–30, respectively. Correspondingly, the regression model will be trained on the training set and the quantitative analysis will be conducted on the test set, while the correlation tests will be performed using all the timestamps but only for the 57 traffic zones with TOU pricing schemes.

Descriptive statistics of the data used in this study are presented in Table 2. The statistic of pile densities shows that charging piles are more densely distributed in the CBD than in other regions. Judging from the average occupancy rate of 24.50% and 31.46% during daytime and nighttime, respectively, charging facilities are idle most of the time. During daytime in the CBD, the maximum occupancy rate is less than 100%, indicating that EV users can access charging piles if they are willing to pay enough. A possible reason is that the average charging price in the CBD is 6.19% higher than that in other regions, effectively moderating the demand. By contrast, although the charging load is concentrated during the nighttime, with the highest average occupancy rate and in-use pile number at 33.85% and 26.70, respectively, its average charging price is only 0.90 CNY per kilowatt hour (kWh), which is 12.22% lower than the daytime price in these areas. Besides, the number of neighborhoods for each studied traffic zone is counted, indicating a denser distribution of zones within the CBD. Changes in EV charging demand for each zone are expected to spread through their neighboring zones, and this study aims to demonstrate and reveal the pattern of these changes caused by price fluctuations.

Several configurations of the impulse response analysis should be noted. First, in order to avoid misinterpretations caused by over-fitting, the studied period is set to 13–18 July, 2022, i.e., the test set, where the data are new to the regression model. Second, since price-induced changes in demand are not immediately observable in practice, a time lag is required to estimate the effects. Considering the average travel time of approximately 36 min in Shenzhen reported in the 2022 Annual

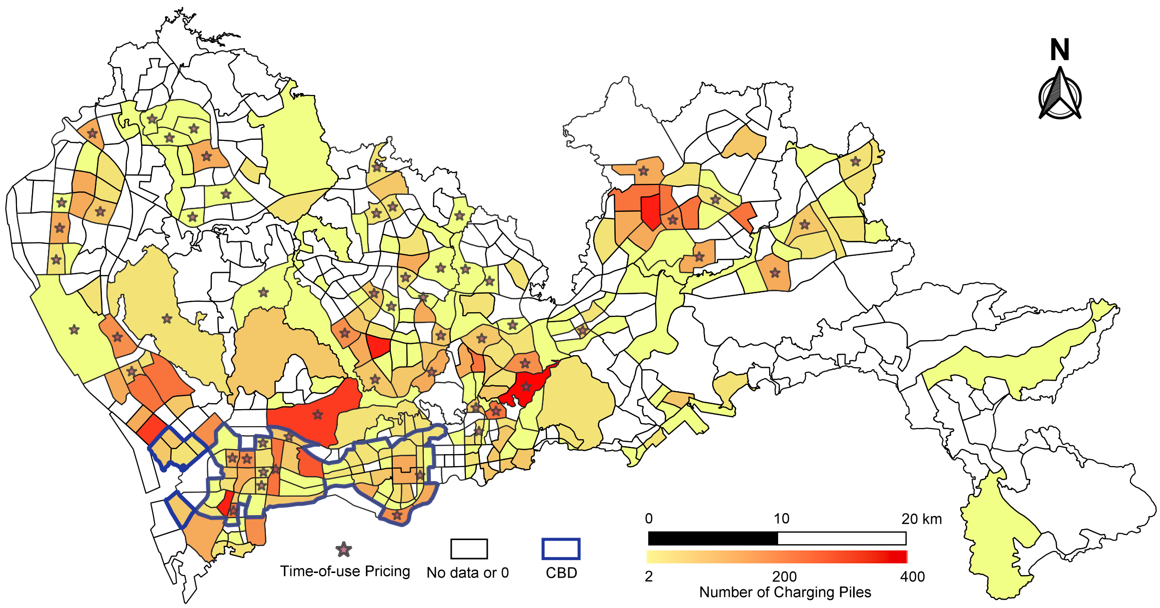

Fig. 3. Spatial distribution of public EV charging pile distribution in Shenzhen.

Table 2
Descriptive statistics of Shenzhen's EV charging dataset.

Region		Occ.	Occ. rate	Price	Occ.*	Occ. Rate*	Price*	Pile density	N_neighbors
CBD	ave	20.16	24.18%	1.03	19.65	24.33%	1.01	99.07	5.23
	std	20.14	14.45%	0.12	18.33	14.11%	0.14	73.37	1.67
	min	0.00	0.00%	0.70	0.00	0.00%	0.51	36.67	2.00
	max	130.00	92.68%	1.34	110.00	82.43%	1.34	289.47	11.00
Others	ave	18.44	24.61%	0.97	26.70	33.85%	0.90	30.90	3.69
	std	20.63	15.53%	0.17	30.51	19.84%	0.21	27.97	1.83
	min	0.00	0.00%	0.54	0.00	0.00%	0.25	0.04	0.00
	max	181.00	100.00%	1.47	220.00	100.00%	1.35	130.12	10.00
Overall	ave	18.87	24.50%	0.99	24.93	31.46%	0.93	42.86	4.07
	std	20.52	15.27%	0.16	28.12	19.02%	0.20	47.56	1.91
	min	0.00	0.00%	0.54	0.00	0.00%	0.25	0.04	0.00
	max	181.00	100.00%	1.47	220.00	100.00%	1.35	289.47	11.00

Occ. is the abbreviation for occupancy;
The headers without * indicate the daytime data (i.e., 8 am–8 pm), while the headers with * represent the nighttime data (i.e., rest of the days);
The units of Price and Pile density are [CNY/kWh] and [piles/square kilometer], respectively.

Commuting Monitoring Report for Major Cities in China (CAUPD, 2022), the model for 30-min prediction is employed as the backbone for our quantitative analysis, the reliability of which has been demonstrated in our previous work, i.e., Qu et al. (2024). Third, positive and negative price impulses of comparable magnitude to the standard deviation of local price changes are deployed in the 57 traffic zones with time-of-use pricing schemes, i.e., $\Delta c = \pm \mathrm{std}(c)$. As a result, 196,992 (57 traffic zones × 2 impulses × 6 days × 288 time steps at 5-min intervals each day) data pairs of price impulses and corresponding occupancy responses can be obtained, which are sufficient for data analysis. The data are shared on this Github link: https://github.com/IntelligentSystemsLab/ST-EVCDP.

Some neural network settings are listed below. First, the maximum epoch for pre-training is 200, and the maximum epoch for fine-tuning is 1000. Furthermore, an early stop mechanism is used, where training is stopped early when the validation set loss does not decrease for more than 100 epochs. Second, The learning rate is set to 0.005 for pre-training and 0.001 for fine-tuning, respectively. Third, proportion of pseudo-samples in the eth round of pre-training is set to $1 - e/1000$, which allows the proportion of pseudo-samples in the pre-training process to be progressively reduced, and the model progressively learns the patterns in the data itself. Fourth, the look back window size is 12 intervals, i.e., the model backtracks 60 min for prediction. Fifth, two hyperparameters are set based on previous studies, i.e., the number of attention heads and the number of GAT layers, which are 4 and 2, respectively. This means that only 1-hop neighbors and 2-hop neighbors need to be concerned for the spillover effect is assumed, and subsequently the results prove that this assumption holds.

5. Results

With the above dataset and specific settings, the evaluation results show that the applied model can reduce the prediction errors significantly with the highest scores in all four evaluation metrics, i.e., Root Mean Square Error 0.1811, Mean Absolute Error 0.3220, Mean Absolute Percentage Error 16.87%, and Relative Absolute Error 19.63%. Compared to the Vector Auto-Regression (VAR) model (Inoue & Kilian, 2013), which is widely used in Econometrics for data analysis, the applied model has an accuracy improvement of 61.3% (i.e., the average improvement in the four metrics). Compared to the state-of-the-art models for spatio-temporal traffic condition prediction, i.e., DCRNN (Li et al., 2018) and AST-GAT (Li & Lasenby, 2022), the accuracy improvement is 5.9%. More importantly, the evaluations on model interpretations demonstrate that the applied model is plausible in handling price fluctuations and spillover effects.

In the following subsection, the results of correlation and causality tests will be discussed to identify the relationship between EV charging

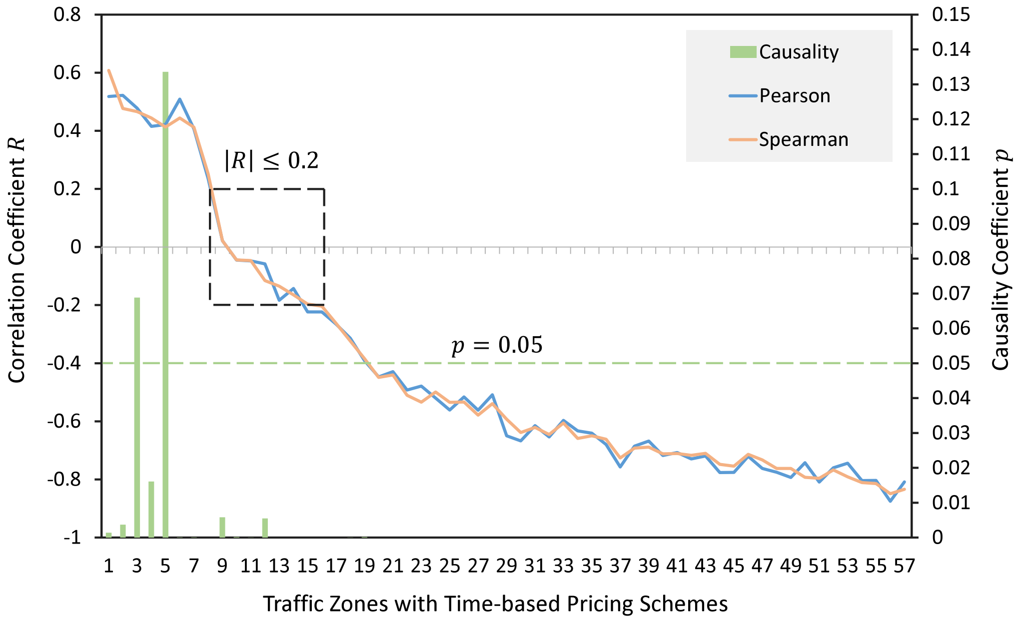

Fig. 4. Results of correlation and causality tests.

occupancy and price. More importantly, the results of impulse response analysis based on our deep learning regression model will be analyzed to quantify spatial and temporal impacts of price on EV charging demand.

5.1. Determination of the correlation relationship

Fig. 4 shows the results of correlation and causality tests, where the black dashed box and green dashed line indicate the judgment conditions, respectively. It can be seen that only two zones have Granger causality coefficients higher than the threshold of 0.05. In other words, a Granger-causal relationship between charging price and occupancy can be assumed with a confidence level of over 95% in most (55 out of 57) of the traffic zones with time-of-use pricing schemes. In contrast, six and seven zones fail the Pearson and Spearman correlation tests, respectively, but they do not overlap with the two failed zones in the causality test. Considering that all the 57 studied zones pass one of these tests and the average absolute values of Pearson's and Spearman's coefficients are 0.5439 and 0.5437, respectively, it can be concluded that EV charging load and price are strongly correlated.

In order to reveal whether the positive or negative correlation between EV charging demand and price in a specific traffic zone is related to its location, a price distribution map with PCC values for the 57 studied zones is drawn, i.e., Fig. 5, where the studied city, Shenzhen is simply divided into the Central Business District (CBD) and other regions. The figure shows that approximately 14% (8 out of 57) of the studied zones have Pearson and Spearman correlation coefficients greater than 0.2 (i.e., the red boxed zones), while about 74% (42 out of 57) have the coefficients less than -0.2. Notably, most (7 out of 8) of the positively-correlated zones are located in the CBD. In contrast, most of the negatively-correlated zones are scattered across the city but rare in the CBD. Such a discrepancy is partly due to the travel habits of the general public: people go to the CBD for activities (e.g., working and shopping) during the day and return to their residential areas in the evening. Moreover, according to the data statistics in Table 2, the daytime prices are generally higher, whether in the CBD or not. This may be due to the fact that, on the one hand, electricity providers encourage charging to be performed at night in order to prioritize industrial electricity consumption and promote valley-peak balancing, and on the other hand, charging providers want to be more profitable during daytime peaks. Taking a studied zone located in the CBD as an example, its occupancy changes and daily price scheme during 19–26 June 2022 are shown in Fig. 6, where the two curves show an isotropic pattern, i.e., high during the day and low at night. On the contrary, charging occupancy in the traffic zones outside the CBD generally peaks at night, leading a negative correlation relationship with charging prices.

In summary, there is a strong correlation between EV charging occupancy and price, with mean absolute values of 0.5439 and 0.5437 for Pearson and Spearman coefficients, respectively. Such a conclusion suggests that the study deserves to be continued rather than terminated early. Furthermore, although the values of correlation coefficients differ across traffic zones, a common pattern can be found, i.e., EV charging demand is mostly positively/negatively correlated with price in transportation areas located in the CBD/other regions.

5.2. Quantification of the spatio-temporal impacts

In this subsection, the impulse response analysis is conducted to quantify the spatial and temporal impacts of price on EV charging occupancy, which can be divided into two parts, namely calculating price elasticities of demand for EV charging in the 57 traffic zones with time-based pricing schemes and estimating the spillover effect among adjacent zones.

5.2.1. Price elasticity of demand

In order to quantify the price-induced changes in occupancy, the price elasticities of demand for EV charging are calculated among the 57 traffic zones with time-based pricing schemes. Accordingly, a pairplot is drawn as shown in Fig. 7, where the subplots on the main diagonal illustrate the Kernel Density Estimations (KDE) of corresponding features, and the rest subplots show the scatters between price impulses, occupancy responses, and the price elasticities. First of all, the subplot **a** shows a Gaussian distribution, indicating that the price impulses in this study are chosen reasonably. On the one hand, this suggests that the strength and number of positive and negative impulse added to the model are equal. On the other hand, this suggests that the strength of the impulse is consistent with the assumption that price adjustments for actual wide-scale business behavior are distributed in accordance with a Gaussian distribution. Subplot **e** illustrates the distribution of the demand response of the dataset in facing a price impulse distributed as in subplot **a**. This illustrates that the negative

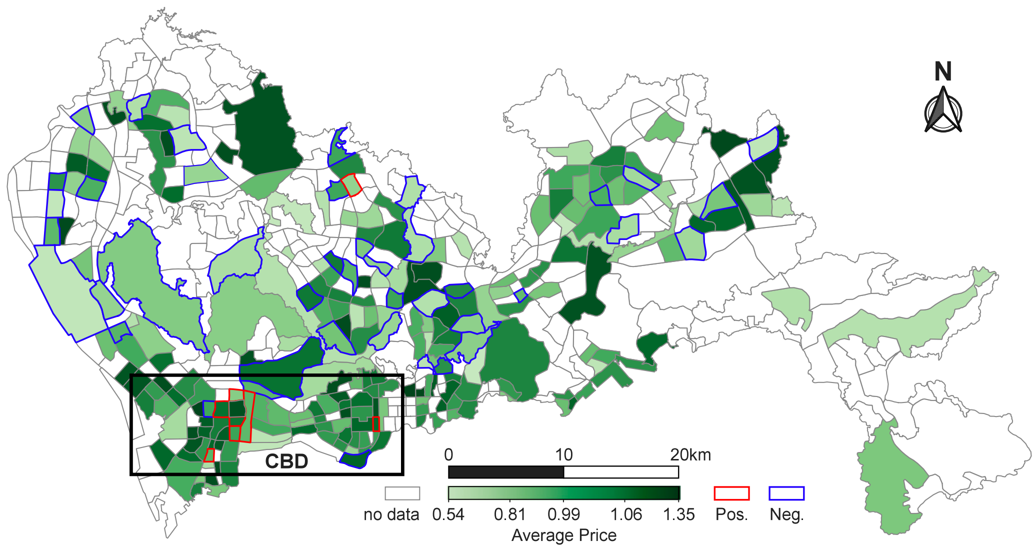

Fig. 5. Map of EV charging price distribution. Pos. (or Neg.) indicates that in a certain zone, EV charging occupancy and price are positively (or negatively) correlated, i.e., the two correlation coefficients greater than 0.2 (or less than −0.2). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

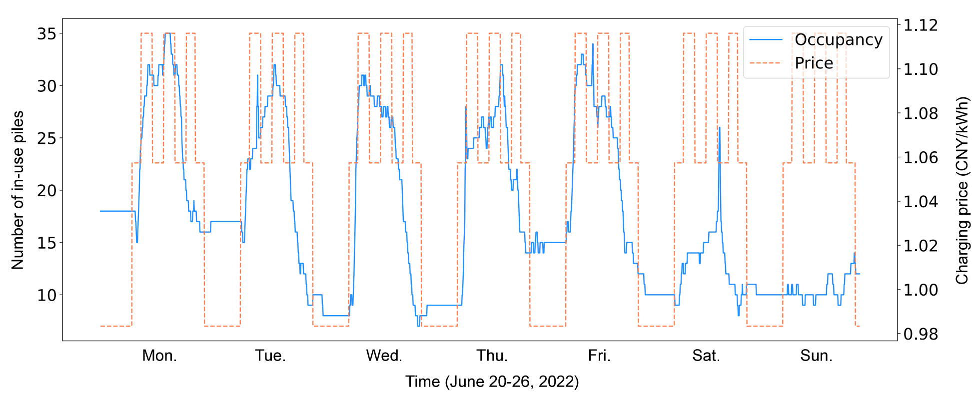

Fig. 6. Lineplot of the occupancy variation and pricing scheme of a traffic zone located in Shenzhen's CBD.

response is more drastic than the positive response, a conclusion that is corroborated by the subplots **c** and **g**. Subplot **i** shows the distribution of the revealed price elasticity of demand, which is consistent with the subsequent paragraph and Fig. 9 and will be described in detail later.

Then, it can be concluded from the subplots **b** and **d** that there exists a negative and linear correlation between occupancy response and price impulse, which is consistent with the common sense that an increase in price will lower demand. The same conclusion can be drawn from the subplots related with elasticity, i.e., **c**, **f**, **g** and **h**, from which the average price elasticity in Shenzhen is estimated at −0.7581, indicating the low responsiveness of EV charging occupancy to price changes. The price elasticity of demand for charging in CBD and non-CBD regions was estimated to be −0.7236 and −0.7654, respectively. The variances for all regions, CBD, and non-CBD regions are estimated to be 0.1016, 0.0683, and 0.1037, respectively. This illustrates the more concentrated distribution of price elasticity of demand in the CBD region, which can also be illustrated in subplot **i** and in Fig. 9. Because the sample size is large, the estimated average value has a confidence interval of $[\bar{x}-10^{-6}, \bar{x}+10^{-6}]$ at a confidence level of 95%, where $\bar{x}$ denotes the sample mean. In this case of inelastic demand, rational managers aiming at revenue maximization would choose to raise the price to a unit elasticity, i.e., −1. Thus, the elasticity estimated by this study demonstrates the Shenzhen government's efforts to keep EV charging price down in order to promote the use of EVs. However, compared to the price elasticity of demand for Gasoline Vehicle (GV) refueling estimated by Rivers and Schaufele (2017) (i.e., −0.40), the price elasticity of demand for EV charging is higher, showing the inferiority of EVs in user dependence on GVs. The price elasticity of demand for EV charging in Shenzhen is also higher than that for a broad sector electricity including residential electricity, and industrial electricity (Datta & Das, 2023). This may be due to the large number of commercial EVs in Shenzhen, including engineering vehicles and cabs, whose users are sensitive to charging prices due to the need to control costs.

Worth noting that simply lowering prices is proven to be inefficient to make the EV charging demand more elastic to electricity prices according to the subfigures **c** and **g**. It can be seen that the negative price impulses marginally change the elasticity, while the positive ones make EV charging users more price sensitive. Charging prices in China are significantly lower than in other regions due to the Chinese government's encouragement for developing electric vehicles and charging services. So further downward adjustments for sufficiently low prices may be difficult to bring about a stimulus to the consumer. Therefore, it is recommended to develop more researches on smart pricing strategies to promote EV charging for renewable energy transition.

To further reveal the price impact at different time and place, a lineplot as shown in Fig. 8 is drawn, illustrating the average elasticities for the traffic zones located in the CBD, other regions, and the whole city during the test set (i.e., July 13–18, 2022). Specifically, the average price elasticities for CBD and other regions are estimated at −0.7236

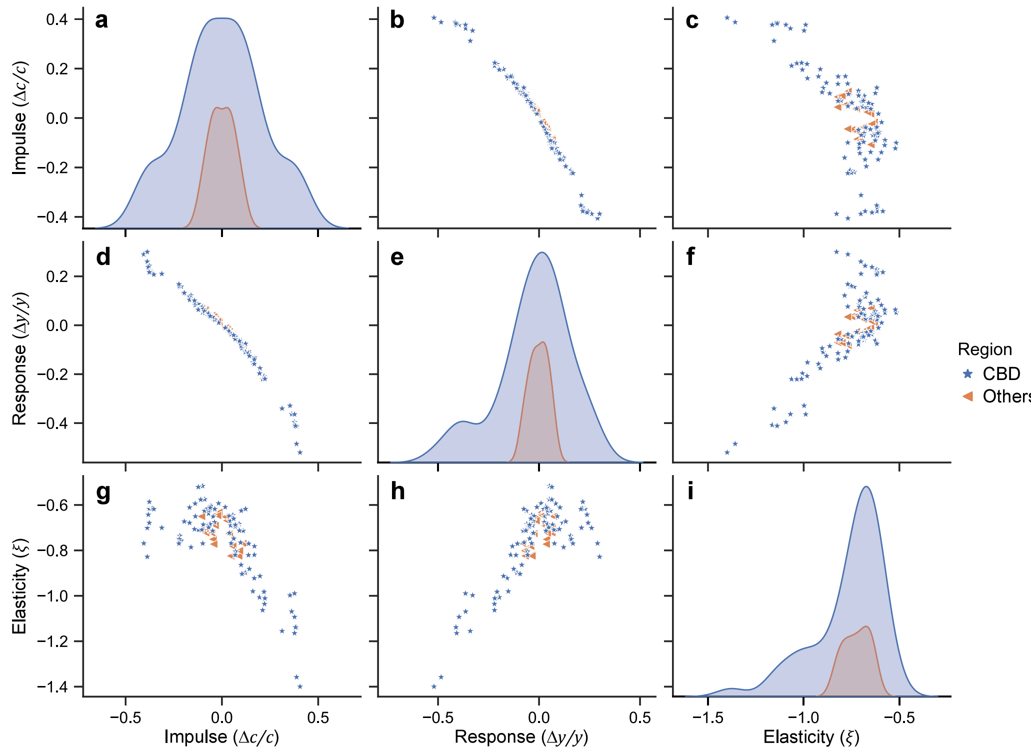

Fig. 7. Pairplots of price impulse, occupancy response, and price elasticity of demand for EV charging.

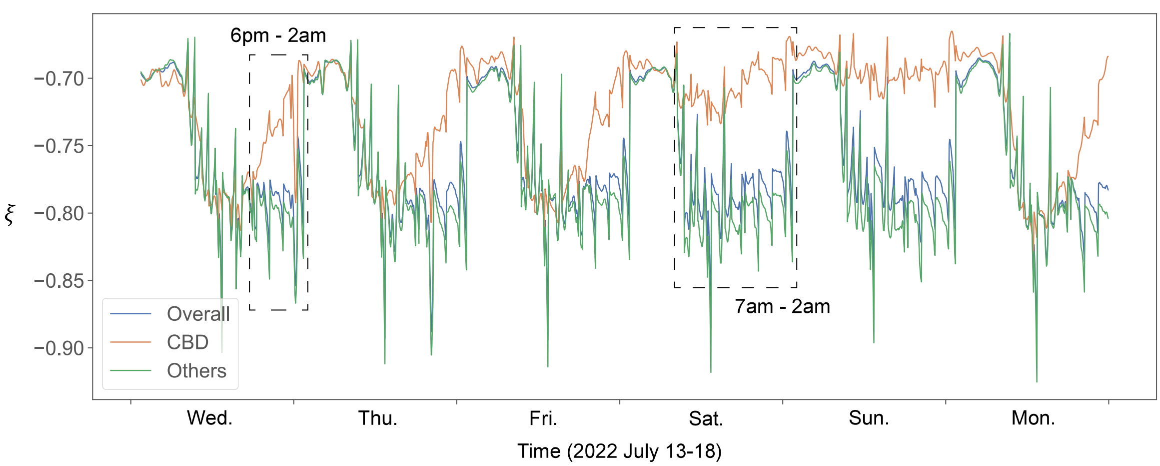

Fig. 8. The average price elasticity of demand between July 13 and 18, 2022.

and −0.7654, respectively, indicating that the charging demand in the CBD is slightly more inelastic to price than that in other regions. Such a discrepancy can be mostly reflected in two time periods, namely 6 pm–2 am on weekdays and 7 am–2 am on weekends, as shown by the two boxes in the figure. During weekdays, it can be seen that demand in the CBD becomes progressively inelastic from about −0.8 to −0.7 during 6 pm–2 am. In contrast, the elasticity for other regions fluctuates around −0.8 at the same period but has a steep inelastic change to −0.7 at 2 am. It is partial due to a common commuting behavior in urban areas, i.e., people leave work at 6 o'clock, head downtown for recreational activities, and return to residential areas in the evening. For a similar reason, the CBD demand for public EV charging is less elastic to price than other regions under weekend conditions. Besides, it can be seen that the elasticities of CBD and others have in common at night (i.e., 2 am–7 am), at which time they are estimated to be around −0.7. According to the data statistics in Table 2, the majority of charging demand occurs at night, indicating the importance of nighttime pricing strategies. While nighttime charging is already less expensive than daytime charging, it is recommended that a cheaper public charging is needed and effectively implemented in corresponding regions, to encourage EVs to charge when the city's electricity demand is low (i.e., at night).

The price demand elasticity is different at different occupancies, as illustrated in Fig. 9. This scatterplot shows the price elasticity of demand at different occupancies for 57 time-of-use pricing zones over the studied period. When the areas' occupancy is relatively low (below 15%) or relatively high (above 70%), the areas' charging service is inelastic, i.e., users are not sensitive to price adjustments. The elasticity of charging services has a wide distribution when occupancy of charging piles in an area is 15%–70%, i.e., some areas are elastic and others are inelastic, with elasticity values ranging from −0.013 to −1.877. When charging pile occupancy is high in an area and many users are required to charge, it is difficult for these users to divert to other areas or times to accommodate price adjustments. When charging demand is at medium

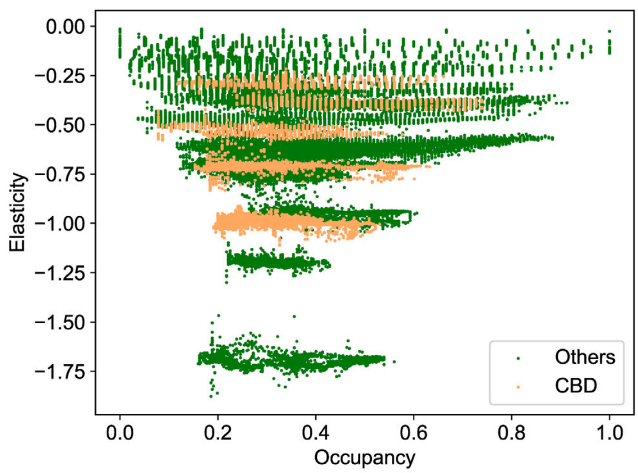

Fig. 9. Price elasticity of demand at different occupancies in time-based pricing areas.

intensity, it proves to be more effective to use a flexible dynamic pricing strategy that directs users to increase or decrease their charging demand in order to meet the grid's valley-peak balance. Moreover, CBD zones are less elastic than other zones, a conclusion that is drawn in the previous subsections and illustrated again in this scatterplot. A study in Beijing, China, noted that the variation in the price elasticity of demand for EV charging is wide-ranging, from −0.2 to −1.5 (Bao et al., 2021). And it also points out that EV charging is typically inelastic during peak times. This subsection shows that similar conclusions are obtained in Shenzhen, China.

To recap, several noteworthy phenomena are revealed in this section, namely, Shenzhen's price elasticity of demand for public EV charging is estimated to be -0.7581; compared to other areas, the public charging demand for EVs in the CBD is less elastic, and such a difference is concentrated in non-working hours; the majority of people choose to charge at night, when it is more affordable, resulting in more inelastic demand in response to price than that during the day; users are price sensitive at medium intensity demand of area charging and relatively insensitive at low or high area demand. Findings indicates that implementing different pricing strategies at different times and in different areas can be helpful for vehicle electrification and electricity network sustainability.

5.2.2. Spillover effect

Due to the conservation of demand for public EV charging (Liu & Liu, 2023), a local change in demand will, to some extent, cause corresponding changes in its surrounding areas. For instance, if the price in one area goes up, EV drivers will tend to park in other areas as an alternative, especially the neighbors. Although such a spillover effect is well known, but it has not been quantified yet. To fill this gap, the occupancy changes in 1-hop and 2-hop neighbors are calculated and compared to the local responses. Accordingly, two stacked percentage bar plots are drawn as shown in Fig. 10, illustrating the impacts caused by positive and negative price impulses, respectively. The upper subplot shows that in the case of increasing price, the sum of 1-hop neighbor responses can almost counterbalance the local response. Specifically, the magnitude of 1-hop spillover η' caused by positive price impulses is estimated to be 89.48%. Considering that the 2-hop neighborhood receives almost no impact ($\eta'' = 0.63\%$), it can be assumed that the equivalent of about 10% of local demand changes would be reduced from a cross-zone perspective. Conversely, the lower subplot shows that the decrease in occupancy between 1-hop adjacent traffic zones is only half the value of the increase in local occupancy ($\eta' = 53.88\%$), while the 2-hop neighbors are basically unaffected as well ($\eta'' = 0.35\%$). It indicates that about 50% of the increase in local demand would come from surrounding areas, in the case of lowering charging prices. These findings corroborate with the finding in Section 5.2.1 that EV users in Shenzhen are more sensitive to price increases compared to price reductions. In a newly published study in Shenzhen's Longgang central district, a 5%–15% charging price increase could result in a 20%–40% loss of demand to 1-hop neighbors, but the percentage of loss to 2-hop neighbors is extremely rare (Kuang et al., 2024). The conclusions obtained in this subsection are similar to the previous study, but the scope of our current study is larger.

To quantify the scope of the spillover, Fig. 11 is drawn, in which the average 1-hop and 2-hop responses are categorized by location (i.e., CBD and Others) and impulse direction (i.e., positive and negative). The figure shows that the cross elasticities of 1-hop neighbors are much greater than that of 2-hop neighbors, with the average values of 0.5667 and 3.70×10^{-5}, respectively. Furthermore, while it shows that 1-hop neighbors are more sensitive to price increases in the source zones than price decreases, it cannot have a similar conclusion from the perspective of distance, i.e., the impact from price increases can propagate farther. Therefore, it can be argued that adjacency is more important than distance in demand spillover. Even if an area is very close to the price-changing area, it can be virtually unaffected by the price fluctuations only if there is a buffer zone between them. Nevertheless, in industrial practice, a simple and clear range of influence is very instructive for urban EV charging policy development. Using the discriminator introduced in Section 3.3, the scope of price-induced demand spillover r is estimated at 3.45 km, which is about 4 times the 839 meters walking distance for public travel in Shenzhen (CAUPD, 2022).

In summary, the spillover effect of EV charging demand caused by price fluctuations is quantified from two aspects, i.e., magnitude and scope. The magnitudes of demand spillover induced by positive and negative price impulses are 89.48% and 53.88%, respectively, while the radius of spillover is estimated to be 3.45 km. The finding can inform not only pricing strategies but also related infrastructure planning.

6. Discussion and conclusion

6.1. Discussion

The significant correlation relationship between EV charging demand and prices identified in this study supports that electricity price can be an effective demand-side policy tool to balance EV charging demand and supply in urban areas. Based on the above findings, relevant policy recommendations are put forward as follows.

(1) Smart pricing strategies for EV charging services are promising for the energy transition. Although the public EV charging demand is inelastic to price fluctuations, it is much more elastic compared to gasoline vehicle refueling. This means that consumers' charging behavior can be effectively influenced by adjusting the price.
(2) Our discussion on the spatio-temporal variation in the price elasticity raises the need to study the smart pricing strategies for EV charging from different perspectives, i.e., weekdays and weekends, daytime and nighttime, CBD and other regions. It indicates that providing cheaper public charging for EVs during off-hours is more conductive to vehicle electrification than in working hours, as users are more price sensitive at this time and encouraging charging during off-hours can relieve pressure on the grid at busy times..
(3) Considering the urban power grid and transport system as a unified whole, our findings on the spillover effect between adjacent areas enable governments to formulate a comprehensive policy of adjusting prices. For example, if the price in one area is adjusted upwards, it may on the one hand lead to an increase in demand for charging in neighboring areas and on the other hand

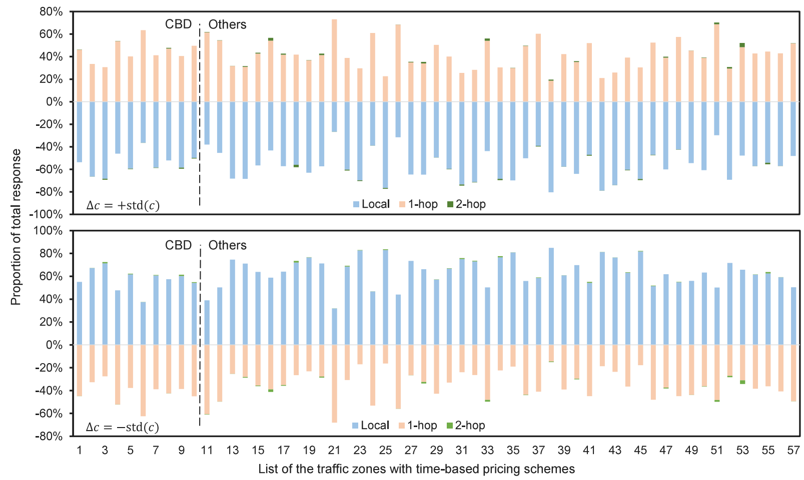

Fig. 10. Spillover of the price-induced changes in public EV charging demand between adjacent traffic zones.

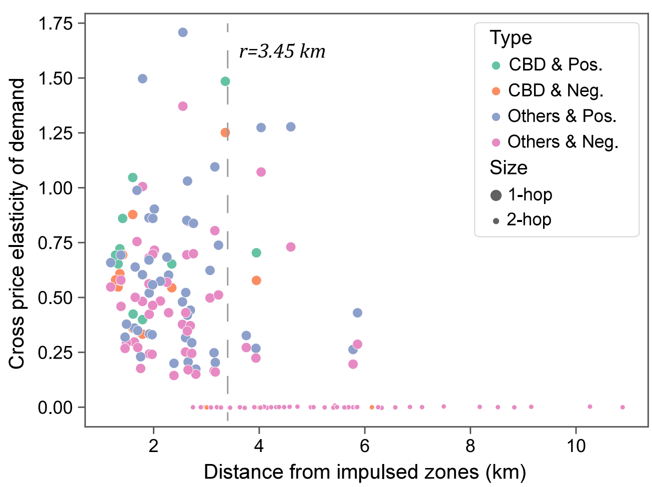

Fig. 11. Distribution of the average responses and distances among neighboring zones.

bring unnecessary cruising and road usage. Therefore, moderate price adjustments need to be implemented in neighboring areas to avoid excessive demand shifting and overloading of charging infrastructure. Besides, the study shows that blocking the impact of price fluctuations on public EV charging behavior by building buffer parking areas is feasible and effective.

6.2. Conclusion

Based on a dataset of the usage status and price of 18,061 public plug-in charging piles in Shenzhen, China, from June 19 to July 18, 2022, the spatio-temporal impact of electricity prices on EV charging occupancy in urban areas is quantified. The results reveal several important findings. First and foremost, the price elasticity of demand for public EV charging is estimated to be −0.7581. It can be concluded that the EV charging demand in Shenzhen is inelastic with respect to electricity prices. Morever, it can be seen that the negative price impulses marginally change the elasticity, while the positive ones make EV charging users more price sensitive. Second, it can be found that the magnitudes of the spillover effect are 89.48% and 53.88% in the case of rising and falling prices, respectively, indicating that EV drivers are more sensitive to price increases than reductions. Third, it can be found that the spillover scope is 3.45 km, since 95% of the studied traffic zones within the scope have a cross-price elasticity greater than 0.1. Meanwhile, 2-hop neighbors are found to be marginally affected by the price impulses, highlighting the significance of buffer zones in blocking impact propagation. In addition, the elasticities in the CBD and other regions are estimated at −0.7236 and −0.7654, respectively. Although they fluctuated consistently around −0.7 and −0.8 during two time periods, namely 2 am–7 am daily and 8 am–6 pm on weekdays, demand for EV charging in the CBD is more inelastic to prices during 6 pm–2 am on weekdays and 7 am–2 am on weekends. To the best of our knowledge, this is few studies to estimate the essential econometric indicator (i.e., price elasticity of demand) and the complex spillover effect of public EV charging in urban areas.

Future work can be conducted in two directions. First, although plenty of studies have proposed dynamic pricing and co-pricing strategies for EV charging, an integrated strategy that combines the both concepts is still missing. Using the quantitative estimation results of this paper, a dynamic co-pricing strategy can be developed that considers not just local but also spillover effects. Second, further research is expected to quantify the price elasticity of demand for EV charging in other cities worldwide, which may provide profound implications for measuring the development of vehicle electrification globally.

CRediT authorship contribution statement

Haoxuan Kuang: Writing – original draft, Visualization, Validation, Software, Methodology, Conceptualization. **Xinyu Zhang:** Writing – original draft, Visualization, Methodology. **Haohao Qu:** Writing – original draft, Visualization, Methodology, Data curation. **Linlin You:** Writing – review & editing, Methodology, Data curation. **Rui Zhu:** Writing – review & editing, Methodology. **Jun Li:** Writing – review & editing, Supervision, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We have shared the link to our data.

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