Research on charging facility distribution in London

Social and Geographic Data Science

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Introduction

Since the 20th century, the rapid greenhouse gas emissions have affected the climate and human living. The transportation sector contributes 13.1% greenhouse gas emissions worldwide and more than two thirds are generated from road transport (Pollet, Staffell & Shang, 2012). In that case, low- and ultra-low carbon technologies should be concerned and improved, especially for automotive industry (Contestabile et al., 2011). Considering the alternative energy demand for transport, the electrification of vehicles has been gradually recognized as the most promising strategy supported by several national governments worldwide (Mazur et al., 2018). However, the insufficient charging network, such as the lack of charging facilities and improper location selection of stations, could be seen as the essential barrier of the EVs popularization in many countries (Harrison & Thiel, 2017 and Csiszár et al., 2019). Considering related policies, European Union (2014) has promulgated the "Directive on the Deployment of Alternative Fuel Infrastructure", mandating that Member States generate appropriate national policy frameworks for the development of electric vehicles (EVs) charging infrastructure.

In London, diesel vehicles are considered as the major lethal air pollution source, contributing to 9400 deaths annually, which should be replaced by sustainable zero-carbon ones (Shammut et al., 2019). According to UK policy, EVs could receive grants equivalent to approximately 35 percent of the vehicle's retail price and exempt from London's Congestion Charge (Contestabile, Alajaji & Almubarak, 2017). Besides, following the EU Directive, UK government committed to match funding for private and public entities for deploying charging points (ibid.). Indeed, the generous incentives to EVs users have stimulated consumer acceptance and accelerate EVs market expansion (Zhou et al., 2014 and Krause et al., 2013). However, the policy only roughly specifies the expected target density of 0.1 chargers/vehicle without necessary investigation on charging facility selection, so that it cannot achieve maximum benefits. Therefore, this essay will judge the rationality of current charging facilities distribution in London and promote suggestions for charging facility location selection for the corresponding policy intervention in future.

Literature review

With the popularization of electric vehicles (EVs) among different countries, the optimal distribution and placement of charging points and relevant elements have been researched in previous studies, considering local contexts and demands. According to Hao & Zhang (2019), belonging to the traffic network, the deployment of charging stations could not separate from the geographical items, including public facilities, crowd density, traffic flows and road conditions. Among these items, public parking places have been proposed as the highly recommended charging locations where car users might frequently park (Ai, Zheng & Chen, 2018 and Csiszár et al., 2019). Besides, home parking places also could significantly contribute to the charging network for EVs (Liu, 2012). Supported by Morrissey, Weldon & O'Mahony (2016), because of the preference of EVs users to charge at home at peak grid demand period, especially in the evening, related departments should introduce corresponding policies to improve public charging infrastructure to achieve diversion. Besides, Csiszár et al. (2019) mentioned the relationship between building functions and charging infrastructure selection. In practices, studies have noticed that people would like to recharge their EVs while working or shopping, which might influence the preference of charging action from temporal and spatial dimensions (Liu & Wang, 2017).

Despite from the land use characteristics, crowd density and traffic flows could influence the traffic congestion and charging facilities planning as well. According to Csiszár et al. (2019), charging infrastructure near concentrated services and high-density regions could support urban public charging demand better. The traffic flows are related to people's travel demand, especially working demand. Therefore, employment status of local residents might affect the potential efficiency of charging facilities. Similarly, Shareef, Islam & Mohamed (2016) also emphasized the importance of site accessibility, local employment status, trip attributes and population density in predicting the appropriate locations for chargers. In addition, another influence factor related to travel demand is the accessibility of alternative public transport system. The public and private transportation could be regarded as complementary transportation systems. According to Ai, Zheng & Chen (2018), transit hubs are usually equipped with fundamental infrastructures for seamless transfer.

Apart from the travel-related features, people' s personal conditions, such as income and demand, also affect the car ownership and further affect the efficiency of charging facilities. As mentioned by Hu et al. (2018), the socio-demographic characteristics, such as population structure and housing price, are all related to consumer purchasing power. Similarly, Csiszár et al. (2019) clarified that the selection of charging stations should concern about the age and employment status of household members as reference. Besides, the willingness to use EVs could also guide the allocation of charging facilities (Csiszár et al., 2019). According to Yi et al. (2019), comprehensively considering the context of local residents could probably avoid the unreasonable deployment of charging infrastructure and corresponding negative results, including low user satisfaction and land resources waste.

Methodology

Data sources & geographical resolution

The National Chargepoint Registry (NCR) from Department for Transport, database of publicly available charge points for EVs in the UK established in 2011, is the data source of charging points registration locations utilized in the analysis. The NCR holds individual records for charging facilities registered for use in the UK, with detailed characteristics, including locations with latitude and longitude, charge device status, registry dates and so forth. Generally, the dataset contains 12332 registrations in which 12139 are still in service. The research chooses London as the study area, which accounts for a third of the dataset. As Figure 1 represents, the charging points number has experienced a sharply increasing trend, reaching 3817 in 2020. According to Transport for London (2019), after the mayoral election in

2016, the following new London Plan has gradually emphasized the importance of the installation of EVs charging infrastructure, which might be the reason of the surge afterwards. Besides, Since 1 January 2018, there was a requirement for all new black taxis in London to be zero emissions (C40 Cities Climate Leadership Group, 2019).

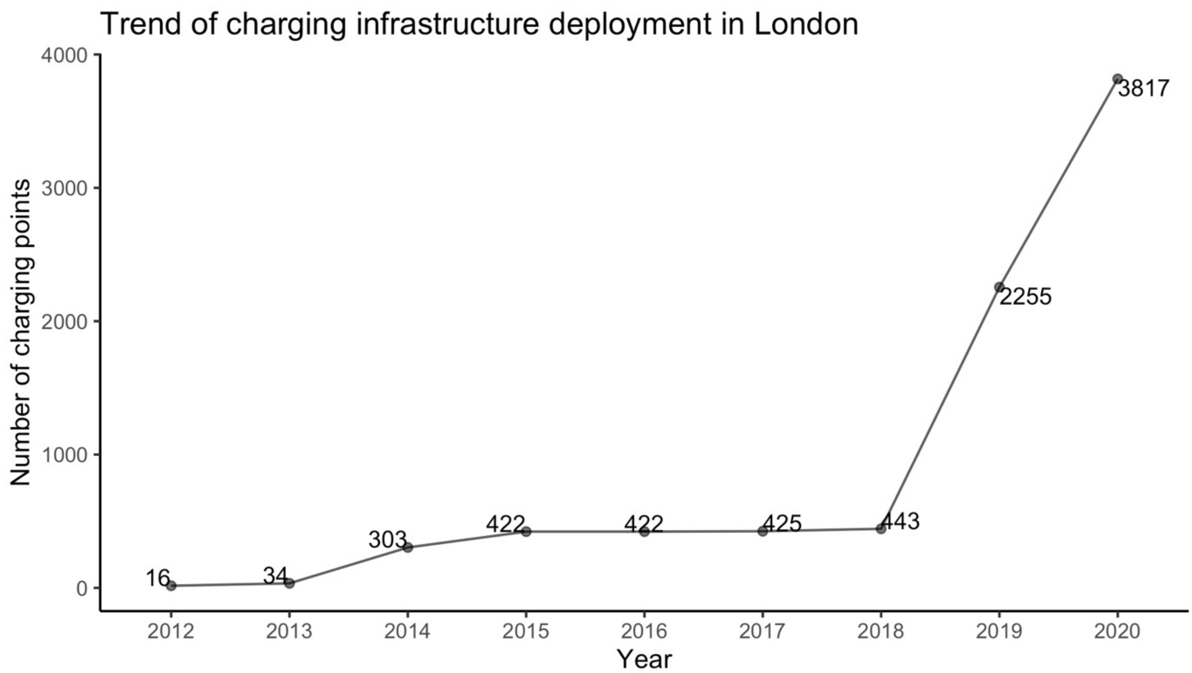

Figure 1: Trend of charging infrastructure deployment in London from 2012 to 2020 (Source: Author’s own)

Statistical analysis

The subsequent paragraphs will produce a comprehensive analysis, consisting of the spatial and non-spatial statistics. Figure 2 has summarized the main workflow of data processing and analysis. At the beginning, the exploratory spatial analysis methodology will be applied to explore the distribution pattern of charge infrastructure in London and visualize the temporal geographical variation. Then, spatial autocorrelation analysis will be used to further evaluate whether there are relationships between the observations of charging stations in particular wards with that in their neighboring wards. Furthermore, in order to forecast charging facility location selection for future, the essay also compare the charge points registration distribution with other characteristics mentioned in the literature review part, including land-use, travel-related and socio-demographic characteristics, applying ordinary least squares (OLS) regression models. In order to achieve higher accuracy for the results, Spatial Lag Model (SLM) which involves a separate spatially lagged variant of the dependent variable as an independent variable of the model (Morton, Lovelace & Anable, 2017), as well as Spatial Error Model (SEM) which incorporates a spatial lag of the OLS regression model's residual as an independent variable (ibid.), all participate in the comparison. Besides, queen and k nearest neighbors (KNN) strategies for evaluating SLM and SEM are all considered.

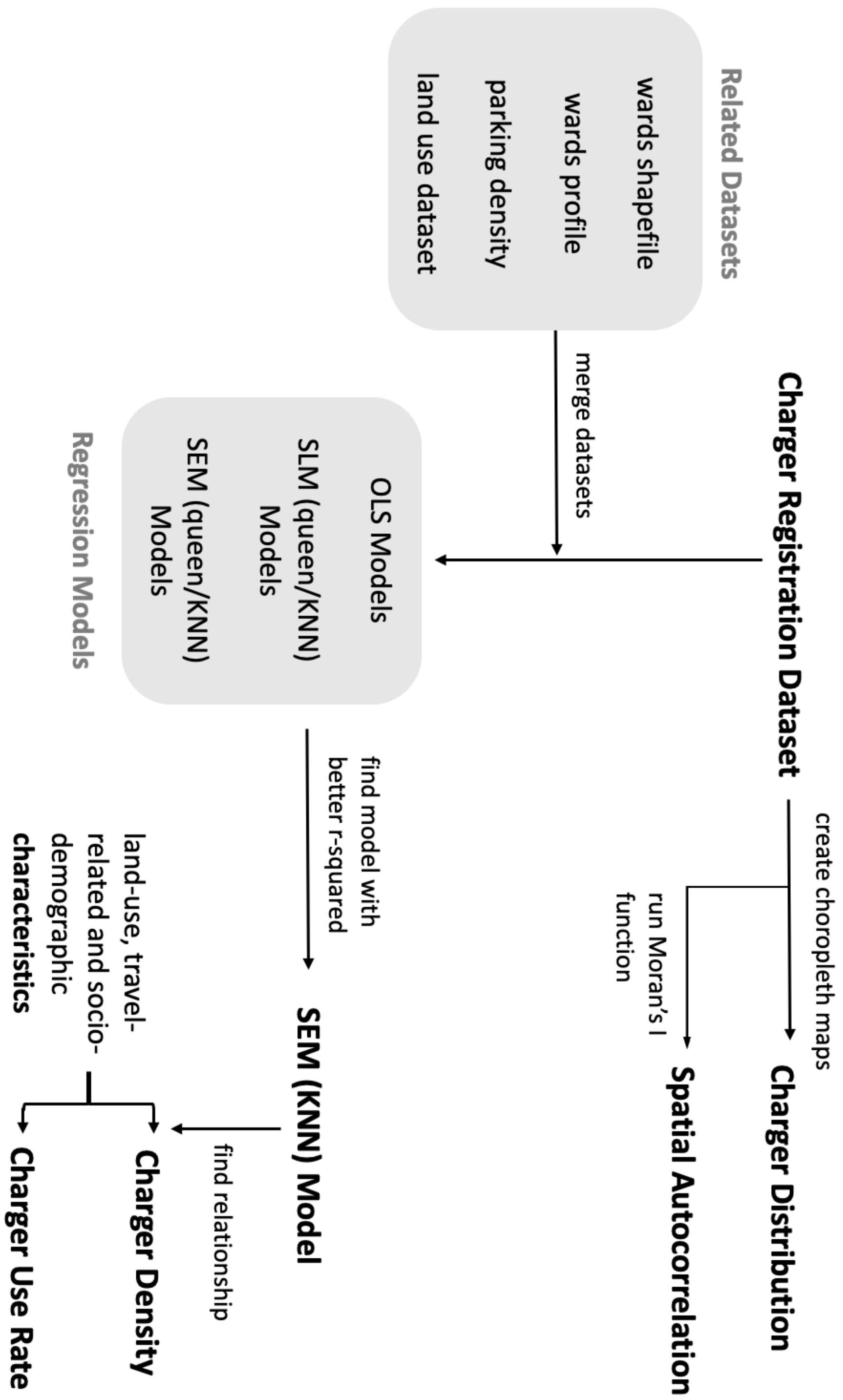

Figure 2: Workflow of data processing and analysis (Source: Author's own)

Results

Descriptive analysis

By locating EVs registrations and visualize the geographical variation, the choropleth maps have been created. In specific, Figure 3 expresses the density of charge points in London in 2018, 2019 and 2020, aggregated at the ward level of UK administrative geography for observing more detailed information. The central areas of London, especially wards in City of Westminster and Kensington and Chelsea, naturally become the development center surrounded by high-density infrastructure districts, with more than 400 charge points per thousand hectares being registered. Besides, although there are a few scattered high-density points, the expansion of charging facilities mainly centers around City of London and its west, the political, financial and cultural center of London.

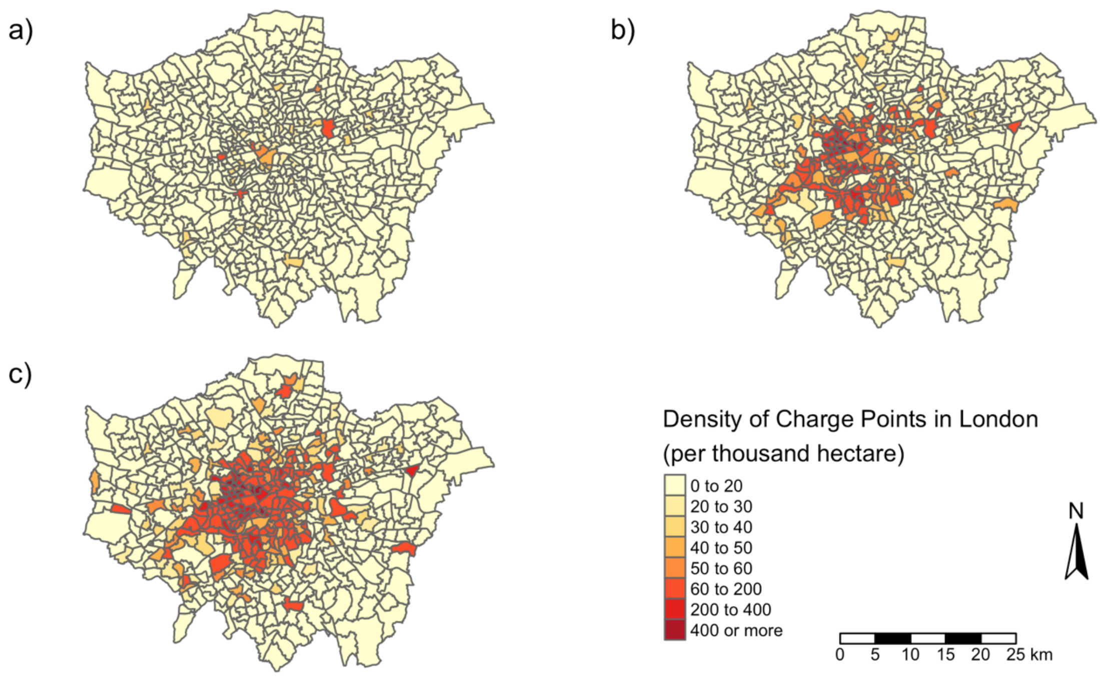

Figure 3: The spatial variation of charge point density in London over years. a) charge point density in 2018; b) that in 2019; c) that in 2020 (Source: Author's own)

Spatial autocorrelation analysis

To explore the potential spatial pattern, Global Moran's I and Local Moran's I statistics for charge points in London were conducted. Table 1 illustrates the Global Moran's I results from 2018 to 2020, which return significant results (p-value < 0.001) in all cases. Specifically, the Moran's I statistic increases from 0.259 to 0.580 and the standard deviation also rises from 11.540 to 25.345, which all indicate that the global spatial autocorrelation gradually becomes highly recognizable phenomenon.

Table 1: Global Moran's I of charge points in London in 2018, 2019 and 2020 (Source: Author's own)

year	Moran's I statistic	Standard deviation	p-value
2018	0.259	11.540	< 2.2e-16
2019	0.524	23.078	< 2.2e-16
2020	0.580	25.345	< 2.2e-16

Furthermore, as Figure 4 shows, Local Moran's I analysis could identify the specific clusters across the whole region. From the results, the clusters of wards with similar and different density of charge points registrations are presented across the London. Among them, the wards shaded different levels of blue represent cold-spot areas, with lower densities of charge points. Conversely, the wards shaded different levels of red represent hot-spot areas, where they display relatively higher densities of charge points. During the recent three years, cold-spot regions mainly scattered and appeared around the outskirts of London, while hot-spot regions mainly aggregated in the central area of London. Besides, it is intriguing to notice that Stratford and New Town in Newham (at northeast) gradually transforms from a ward surrounded by low-high areas to low-high area, and finally become a cold-spot area, which might need suitable policy support.

Another finding is that spatial outliers, such as low-high and high-low areas, are not common, representing by colors of light blue (namely low density in certain ward but high density in the surrounding wards) and light red (namely high density in certain ward but low density in the surrounding wards) respectively. Based on the mapping, Mill Hill of Barnet, Norwood Green of Ealing and Village of Merton have become the newly low-high regions, while marginal wards of Westminster, Wandsworth and Kensington and Chelsea gradually become high-low regions.

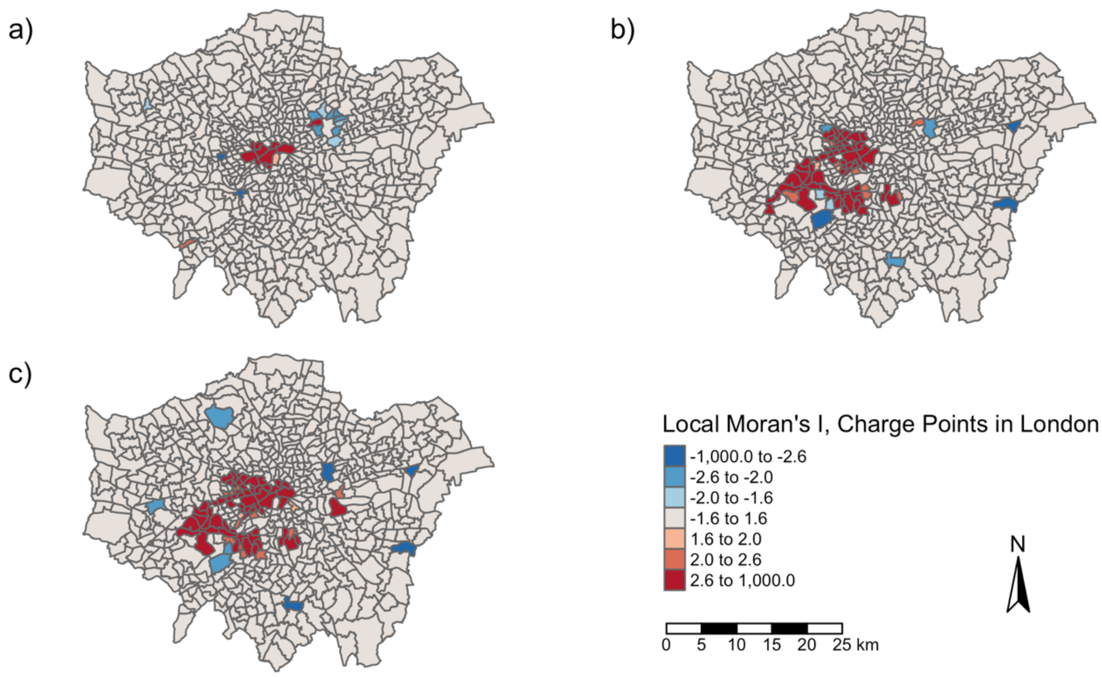

Figure 4: Local Moran's I of charge points in London over years. a) Local Moran's I in 2018; b) that in 2019; c) that in 2020 (Source: Author's own)

Correlation analysis

There are several characteristics are considered to contribute to the density of charge points (CD) and its utilization rates (UR), including socio-demographic, travel-related and land-use characteristics. In specific, they are employment rate (ER), house price (HP), public transit score (PS), which could reflect the level of local public transport), parking density (PD), percentage of residential area (RSP) and percentage of road area (RP). As presented in Table 2, charger density has strong positive relationships with house price, public transit score and percentage of road area, accounting for 0.549, 0.569 and 0.579 respectively. However, the utilization rates could be observed to have relatively strong negative relationships with house price, public transit score and percentage of road area, accounting for 0.339, 0.557 and 0.464 respectively.

In order to conduct regression models in the next step, it is also necessary to check whether those selected characteristics, namely the independent variables of regression models, would correlate with each other. In that case, the operation results of the models would not be interfered by double weight action. The corresponding multicollinearity checking has been showed in Figure 5, which represents few correlation phenomena, in which the reds and blues represent the degree of positive and negative correlation. Among them, the relatively higher one is between RP and PS. However, since the addition of these variables could improve the accuracy of the model, increasing R squared by around 1.5%, they would remain as independent variables of the models.

Table 2: Correlation analysis between chargers related variables (Source: Author's own)

variables	CD	UR	ER	HP	PS	PD	RSP	RP
charger density (CD)	1.000							
utility rate (UR)	-0.478	1.000						
employment rate (ER)	0.031	0.109	1.000					
house price (HP)	0.549	-0.339	0.153	1.000				
public transit score (PS)	0.569	-0.557	-0.186	0.463	1.000			
parking density (PD)	0.279	-0.207	-0.085	0.081	0.302	1.000		
Pct. of residential (RSP)	-0.050	0.212	0.267	-0.100	-0.175	-0.094	1.000	
Pct. of road (RP)	0.579	-0.464	-0.224	0.342	0.761	0.298	0.215	1.000

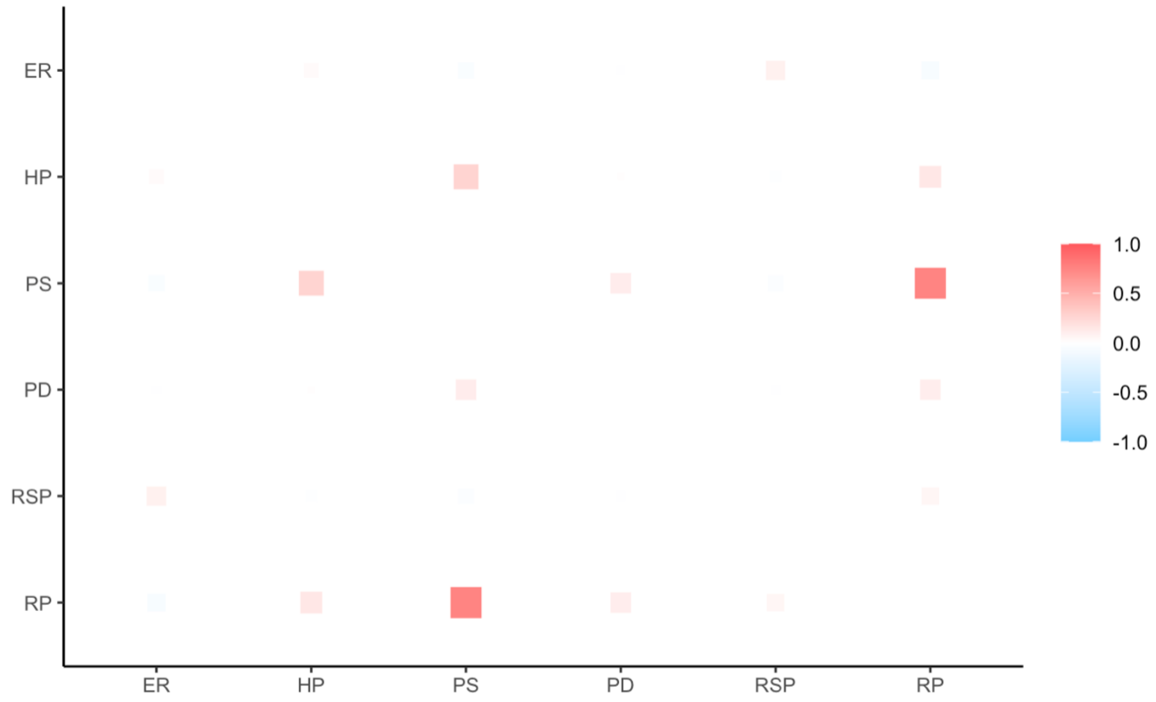

Figure 5: Multicollinearity checking of the independent variables, with reds and blues showing the degree of positive and negative correlation (Source: Author's own)

Regression analysis

As mentioned, the analysis has been built upon the regression models and concerned land-use, travel-related and socio-demographic characteristics as independent variables. Based on the results, future decision-making processes on charging infrastructure deployment could identify the indicators and promote more reasonable strategies or policies. Basically, the research has built two original models first, Model 1 and Model 2, and then create derivative regression models and compare them, in order to find the best fitted model. Model 1 and its derivative regression models aim to identify the relationship between chargers use rate and other characteristics, while Model 2 and its derivative models aim to observe the relationship between charger density and other characteristics.

SLM and SLM results have been compared to observe potential spatial heterogeneity. Besides, two neighboring identification approaches for spatial models, queen and k nearest neighbors (KNN; deciding neighbors by selected number) strategies have been considered. Considering the comparing indicator, R squared (model fit indexes; seen as better fitted with higher value) and Akaike Information Criterion (AIC) (often applied for estimating the out-of-sample prediction error; seen as better fitted with lower value) have been applied. As Table 3 shows, SEM models with KNN strategy is the relatively better one for the prediction of chargers use rate and charger density, with confidence of approximately 60 percent.

Table 3: The comparison between different derivative regression models related to chargers use rate (Model 1) and charger density (Model 2) (Source: Author's own)

	Model 1		Model 2	
	R squared	AIC	R squared	AIC
OLS	0.576	1614.384	0.634	1643.240
SLM (queen)	0.578	1613.629	0.638	1639.875
SEM (queen)	0.580	1612.595	0.642	1636.668
SLM (KNN)	0.585	1605.435	0.647	1626.565
SEM (KNN)	0.586	1605.570	0.649	1626.477

In that case, Table 4 shows the estimation results of SEM models with KNN strategy. As shown, most selected variables are statistically significant (p-value < 0.01), but inconsistent between the two models. Generally, the positive influence factors for charger density include house price, public transit score, parking density, and percentage of road area. However, the effects of these independent variables for chargers use rate represent a completely opposite trend. When the variables represent positively significant effects on charger density, they usually represent negatively significant effects on the chargers use rate and vice versa.

Table 4: Results of SEM models with KNN strategy, showing the relationship between charger density and chargers use rate and other characteristics (Source: Author's own)

	charger density parametric coefficients:		chargers use rate	
variables	estimate	p-value	estimate	p-value
intercept	-14.000***	0.000	21.300***	0.000
employment rate	0.012	0.080	-0.010*	0.015
logged house price	1.010***	0.000	-0.940***	0.000
logged public transit score	1.110***	0.000	-1.100***	0.000
logged parking density	0.112**	0.002	-0.077*	0.030
Pct. of residential	-0.003	0.343	0.024***	0.000
Pct. of road	0.088***	0.000	-0.052***	0.000

Significance codes: '***' 0.001; '**' 0.01; '*' 0.05.

Discussion

It is obvious that the deployment of charging infrastructure across the London wards has presented in a spatial heterogeneous pattern, which is visible in Figure 3. After spatially locating the charging points registrations and comparing conditions of different regions, the chargers aggregated wards, such as City of London and its west, have been noticed. Verified by McCoy (2020), the top five London boroughs for charging points are City of London, Westminster, Wandsworth, Hammersmith & Fulham, Richmond upon Thames, which were all supported by local governments. Besides, on average the population of the City of London and Westminster is the wealthiest group in the UK, easier to invest more on the infrastructure development. In addition, introducing exemption policies for EVs is attractive, specifically for prosperous areas, such as London's Congestion Charge.

From Figure 4, although the occurrence of cold-spot locations seems to be disordered, that of hot-spot always surround the central areas. This phenomenon and the change of Stratford and New Town into cold-spot area might probably be relevant to the spatial flows of EVs. The vehicle preferences of drivers and corresponding policies for the supported infrastructure might influence the neighboring wards, which has also been supported by the by the significance of the spatial elements included in SEM models (see Table 3). Additionally, as mentioned above, Westminster, Wandsworth and Kensington and Chelsea all actively promoted electrification and ranked to the top, which might be the major reason of the occurrence of those high-low regions. According to the possible formation mechanism of cold-spot areas mentioned, those high-low areas might become the newly hot-spot areas.

Several models have been built to identify the relationship between charger density and other characteristics, and between chargers use rate and other characteristics. Overall, the results of charger density model have verified the most observations and recommendations of previous research. More charge points have been deployed in the wealthier wards with higher employment rate, higher public transit system, higher parking density and higher percentage of road. However, considering the chargers use rate, the completely opposite trend indicates that there is an excess of charging facilities in previously suggested areas. This is a warning for London and other regions aiming to invest charging facilities to promote EVs market, meaning that if not adjusting the policies, all regions will be adversely affected. In other words, the areas with more demand for charging facilities would experience a waste of resources, while the areas with less demand will not get the support of policies and lose the opportunity to enjoy equal rights. Therefore, relevant policies must pay relatively equal attention to all regions, without blindly following the previous recommendations.

Conclusion

In conclusion, the essay has represented the current charging facilities distribution in London with hot-spots and cold-spots and investigate the reasons of those results. Besides, in order to determine the relationship between charger density and chargers use rate and other characteristics, the OLS, SLM and SEM models have been compared. After selected the better model (SEM), the results have been explained to judge the rationality of current deployment. Furthermore, the discussion part has pointed out the most serious problem with the existing policies, the excessive policy bias. Therefore, the most important suggestion for the charging facility location selection is that the governments should not only consider the chargers' demand emphasized by previous studies but also its use rate, in order to promulgate more effective polices. As the essay did not consider the effects of charger's quality and national grid, further research should be conducted to obtain more comprehensive understanding for the charging facility locations.

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Declaration of Authorship

I, Anni Huo, confirm that the work presented in this assessment is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Anni Huo

Date of signature: 11 January 2021

Assessment due date: 11 January 2021