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By Lok Wing Chau

DISSERTATION TITLE:

The impacts of infrastructure for electric vehicles on the current urban resources under the Hong Kong Roadmap on Popularisation of Electric Vehicles. Exploring car park crowdedness and electricity consumption from a data science perspective

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ABSTRACT

This dissertation investigates the relationship between the number of first registered electric vehicles and urban resources in Hong Kong, specifically focusing on car park crowdedness and electricity consumption. Data analysis was conducted with the relevant datasets publicly provided by the Hong Kong government, including correlation analysis (after Variance Inflation Factor) and regression with machine learning. Our analysis showed a strong correlation between car park utilisation rate and the number of first registration in electric vehicles (EV). In furtherance, a fluctuated trend in relation the car park utilisation in City Hall was indicated, yet a slight correlation with the first registered EV was detected from four types of electricity consumption. In conclusion, we believe that the increase in the use of EV could potentially impact the car park usage. For electricity consumption, based on our results, the continuous growth of EV is unlikely to significantly influence the existing electricity demand.

DECLARATION

I hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. It is 11562 words in length.

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LIST OF GLOSSARY AND ABBREVIATIONS

Cradle-to-Gate: It is the assessment of a partial product life cycle from resource extraction to the manufacturing stage. It is a tool for minimising the environmental impact of products by applying sustainable production, operation and disposal practices, and it targets to incorporate social responsibility into product development (Cao, 2017).

Electric vehicles (EV): A vehicle that is either partially or fully powered on electric power. In this paper, EV is specifically defined as private electric cars.

Electricity consumption: It is defined by the level of electricity usage, in terms of human and industrial activities, and spatio-temporal and climate conditions (Park *et al.*, 2019).

Green: It refers that the electricity production is produced at low or even zero-emission to the environment. It includes any form of renewable sources such as sunlight, wind, or water. It can also be an adjective to describe an action or a person that hold a primary motive of pro-environmental behaviour (Moisander, 2007).

Greenhouse Gas (GHG): It is a gas that absorbs and emits radiant energy within the thermal infrared range, leading to a greenhouse effect.

Hong Kong Roadmap on Popularisation of Electric Vehicles: This is a government scheme to set out the long-term policy objectives and plan to promote the adoption of electric vehicles by providing incentives in supporting facilities in Hong Kong. It is expected to guide Hong Kong's future direction to attain zero vehicular emissions before 2050 (The Government of the Hong Kong Special Administrative Region, 2021).

One-for-One Replacement: It is a car replacement scheme launched by the Hong Kong government. It is to encourage drivers to replace their conventional-fuelled vehicles with electric vehicles. Incentives include but are not limited to beneficial first registration tax.

Urban resource: The resources that require considerable flows and stocks of resources in a city such as fuel, energy, and land (European Environment Agency, 2015). In relation to the research, it is meant to be EV related. It includes the crowdedness of car parks and electricity consumption by EV charging.

USA: The United States of America

Well-to-wheel (WTW): It is an assessment for overviewing the process of potential pollution from raw material production to car manufacturing, taking into account the emission and energy needed in producing the fuel utilised in vehicles. Also, it associates with car technology operation energy and emission such as tailpipe emissions, other emissions and energy efficiency of the vehicle (gMobility, 2019).

ACKNOWLEDGEMENTS

I would like to thank my supervisor, Dr Valerio Signorelli who provided substantial practical and helpful suggestions for this paper and gave me advice on the areas that I needed to improve during the meetings. This included but was not limited to guiding me to the correct direction, suggest potential areas, and monitor my progress over time.

1. INTRODUCTION

1.1 Market background

In the twenty century, electric vehicles (EV) have been becoming more popular and mature in the car market. The arising of Tesla drew huge attention from the world. In 2020, Tesla was worth approximately 500USD billion which was the aggregated market cap of the nine largest car companies globally (Wayland and Kolodny, 2020). In terms of diffusion, Tesla has delivered nearly 300,000 vehicles worldwide in 2020, meanwhile the sales in China grew spectacularly by about 226% (Dean, 2021; Randell, 2021). The remarkable achievement showed the power and the future of the EV market. Companies with a rich history such as Volkswagen and Volvo are switching their focuses to hybrid/ electric cars rather than diesel and petrol (Volvo, 2018; Riley, 2019).

1.2 Regulations on car emission pushes the shift to EV

It is not solely to enhance competitiveness from a car manufacturers' perspective, but also for meeting and compiling the emission regulations. According to the report from International Energy Agency (IEA, 2020), the vehicle market has been shifting into being more reliable on regulatory and other structural measures on their goods. The use of renewable energy is one of the key measurements. Regulations tend to focus more on the pollution of the surroundings. For instance, governments started to reinforce the restriction of fuel economy standards and promote zero-emission vehicle mandates. Harder punishments are placing on car users and manufacturers. To avoid the emission penalty, both stakeholders have changed to reduce the reliance on conventional cars. Compared to the market in 2016, the EV sales in 2019 exploded to 2.1 million which was around at least a 30% increase during the period (IEA, 2020). It indicates that the EV market has been becoming an important sector, also the vehicle patterns are now transformed from traditional energy fuelled.

1.3 The lack of EV infrastructures

Switching driving habits may be difficult for some groups of people, it could be obstructed by the insufficient infrastructures for EV. Besides the home charger, battery charging stations determine how convenient and feasible EV are (Yang, Guo and Lu, 2018). Western places such as Europe (EU) have a comprehensive agenda about building 1 million public charging stations by 2024 and reach 3 million in 2029 across the bloc (Bannon, 2021). However, the reality is always cruel. There were some criticisms about urban planning that the infrastructure for EV is too sparse in the EU. Based on the findings from the European Court of Auditors (European Court of Auditors, 2021), the promotion of a common Europlug standard charger for EV was successful. Nevertheless, there were no coherent minimum infrastructure requirements to ensure EU-wide electro-mobility. It may occur in a situation where charging stations are concentrating in one place but not generally distributed.

Incomprehensive infrastructure planning is likely to be discouraging towards the popularisation of EV, therefore it becomes a crucial factor for a place that wish to promote it. Eastern countries such as Hong Kong are far behind on both infrastructure and relevant regulations. Unlike other places such as the Republic of China where there are plenty of land resources, Hong Kong is congenitally disadvantageous in planning and building infrastructures. The government also realised the relationship between the shortage of charging facilities and the low motivation in purchasing EV (The Government of the Hong Kong Special Administrative Region, 2019). In fact, FleetNews (Prez, 2021) found that there were more than 59% of interviewees not interested in implementing EV because of the lack of public charging stations. It is currently the biggest barrier to promote the EV market. As a result, the Hong Kong government has launched the 'Hong Kong Roadmap on Popularisation of Electric Vehicles', outlining several long-term policy objectives for promoting the use of EV in Hong Kong (The Government of the Hong Kong Special Administrative Region, 2021).

1.4 Possible areas for investigating the charging network in Hong Kong

For the government plan, one of the objectives is to identify sites for a territory-wide quick charging network. It first brings a motivation to investigate the spatial overview of the current charging network in Hong Kong. In addition, due to the lack of land, most of the chargers are planned to be installed in car parks. Thus, parking usage will be another consideration for the investigation.

The impact of adopting green sources for electricity production is another popularisation focus. Along with the EV's development, people debate that how "green" electric car is. The production of renewable energy could generate sizeable pollutions, which are harmful to the environment. The National Academic Press revealed that producing and transporting renewable energy sources will cause some emissions and pollutants, although it claims to have a relatively low GHG emission and conventional air pollution (The National Academic Press, 2011). Consequently, the popularisation of EV will come with a higher amount of electricity usage, causing EV to become not "green" as its claim. Therefore, electricity consumption could provide some insights into the indirect impact in terms of pollution that EV might bring subsequently.

2. RESEARCH QUESTION

The context of the research question will be based on the recent electric vehicle popularisation roadmap launched by the Hong Kong government. Therefore, this paper is going to investigate ‘the impacts of infrastructure for electric vehicles on the current urban resources under the Hong Kong Roadmap on Popularisation of Electric Vehicles’. Particularly, there are two main urban resources of the research:

1. Car park crowdedness
2. Electricity consumption by EV

3. RESEARCH HYPOTHESIS

A hypothesis needs to be made before defining research objectives. Due to the scarcity of land resources in Hong Kong, the roadmap mentioned that charging stations are going to be installed inside a car park of public/ private buildings (Environment Bureau, 2021). In which, it is difficult to find a publicly available dataset with the exact relevant information of EV chargers from those places. Thus, it is going to assume that the car parking data for this study are all able/ will apply to EV charging stations. In terms of electricity consumption, it is required to assume that there is a proportion of electricity usage by EV coming from the total aggregated figure in the dataset. It is because there is no open dataset on the Hong Kong electricity consumption specifically used by EV (such as charging). These assumptions would be essential for finding the interrelationships between EV and car park usage/ electricity consumption.

4. RESEARCH OBJECTIVES

In order to investigate the parking usage and electricity consumption on EV topic specifically in Hong Kong, there are four main objectives for achieving the conclusion:

1. Gathering literature about the impacts of EV in terms of car park crowdedness and electricity consumption
2. Identify the distribution of the current charging station in Hong Kong
3. Investigate the relationship between the number of first registered EV and urban resources usage
4. Visualising and interpreting the feature(s) with the most significant relationship towards the number of first registered EV

5. LITERATURE REVIEW

The first section of the literature review is going to start with gathering researches that discussed how the introduction of EV provides eco-friendly advantages and the reasons for popularising EV. After that, it will cover papers that stated how the demand for EV has been accelerated by consumer behaviours.

5.1 The benefits of introducing EV

With the introduction of EV, a series of recent studies has indicated that it would help to achieve environmental protection by reducing the use of non-renewable sources. Comparing to traditional energy such as petrol and gasoline, electric cars would produce a remarkably low emission to its surrounding (Holmberg and Erdemir, 2019; Zheng *et al.*, 2020). In respect of the analysis on the well-to-wheel (WTW) emissions of the various types of vehicles, EV outperformed other car types by resulting in the highest efficiency and around 100 g/km less on the CO_2 emissions from the experiment (Eberhard and Tarpenning, 2006). Other scholars (Elgowainy *et al.*, 2010; Moro and Lonza, 2018) also found that the WTW emission of a car with largely electric-powered could be near to zero, meanwhile a mixed power generation EV is comparable to a traditional gasoline-based internal combustion engine car. It shows that the popularity of EV will positively improve the environment by reducing pollution in a place. In regard to the improvement of the air pollution to the surrounding, countries have been fostering and promoting electric vehicles in executing construction of building EV infrastructures such as charging stations in the community (Lee, Garza-Gomez and Lee, 2018).

Studies that discussed spatio-temporal aspects of the EV charging stations is another rare but important view of EV advantages. The location of the charging stations could contribute a more convenient experience for EV users given the same parking habit. It was revealed that EV drivers are able to best utilise the time of parking. Ordinarily, a spatial uncontrolled charging load was categorised as three main states: residential place, work, and others (Shepero and Munkhammar, 2018). In which, most of the cars were investigated as parking more in either workplaces or being driven during the daytime, rather than at home (Freund, Lützenberger and Albayrak, 2012; Galus *et al.*, 2013). With the incentives and schemes that government and public parking places offer, EV drivers can fully minimise the electricity costs and utilise the parking duration for recharging outside the home (Galus *et al.*, 2013). While the adoption of EV brings a higher parking frequency to non-residential buildings, recent research indicated that there was a strong correlation with a high motivation driven by financial objectives for building operators (Fachrizal *et al.*, 2020). It means that car park operators might install more charging plugs to attract EV drivers and to increase their revenues from more parking. Therefore, the popularisation of EV is regarded to provide economic benefits to society as well.

To summarise the paragraphs above, researchers generally have perceived EV as an eco-friendly vehicle due to its benefits such as low emission. Also, another advantage suggested from literature was from the economic perspective. The increasing demand for EV recharging in a car park can potentially bring more motivations for operators to achieve their financial targets.

<u>5.2 Green self-identity underpins the potential demand of the EV market</u>

The eco-friendly purchase behaviour cultivates the EV introduction as well. Given the environmental benefits that EV brings, the adaptation of EV has become the identification of being "green". Green self-identity is a driver of green consumption (Clayton, 2007; Whitmarsh and O'Neill, 2010). Although cultural differences occur when comparing environmental values between consumers in western and eastern countries, people around the world are considering more environmental aspects in their purchase habits. From the experiment in the USA and Korea, it mutually found that there was a positive relationship between self-image congruence and hybrid car purchase intentions (Oliver and Lee, 2010). As a result, the gradual rise of eco-friendly purchase behaviour pushes the progress of EV adaptation and expanding the demand of this market.

Along with the expansive demand for EV caused by the environmental benefits and the facilitation of consumer behaviour, in the next few sections, are going to mention its impacts on urban resources in terms of the context of EV in Hong Kong.

5.3 The subsequent impacts regarding car park crowdedness

Despite the expansion of the EV market will bring economic benefits to non-residential building operators mentioned in section 5.1, the crowdedness of parking slots might be deteriorated along with the popularisation of EV. Given the fact that building charging stations in a car park would provide an advantage of lowering the temperature of the vehicle engine from sunshine during charging, it simultaneously requires EV drivers to park their vehicle longer (Nunes, Figueiredo and Brito, 2016).

It has shown that the parking duration of EV is likely to be longer than cars that are fuelled by traditional energy. From an investigation on EV solar parking lots in the United States, it reflected that vehicles need to be parked for a substantial period during the daytime in order to maximise the benefits of the battery charging performance (Nunes, Figueiredo and Brito, 2016). Depending on the types of connection, the authors showed that an EV charging from empty to full battery could take several hours. It was reported the same idea in another paper, indicating that the charging duration of EV increases significantly than the parking duration of an oil-based fuelled vehicle (Etezadi-Amoli, Choma and Stefani, 2010).

A group of studies has recognised the impacts of EV on car park crowdedness from another point of view, indicating that the voltage of charging stations could influence drivers to park longer (Hawkins, Gausen and Strømman, 2012; Bauer *et al.*, 2015; Tagliaferri *et al.*, 2016; Lombardi *et al.*, 2017; Pero, Delogu and Pierini, 2018; Jenn *et al.*, 2020). They mutually admitted that high voltage (fast charging) comes with various environmental impacts discovered from the life cycle assessment of EV and its use, such as the increase of greenhouse gas (GHG) emission and local air pollutants. Therefore, the typical charging voltage for EV tends to be low. By taking a 15–20 A charger through a 120 V AC plug with around 3.7 kW of power, for example, scholars found that an EV needs eight hours total charging duration for 60-100 km of electric range (Nunes, Figueiredo and Brito, 2016). Consequently, when the number of EV increases, EV will park longer for recharging and result in low parking turnover (Chang *et al.*, 2012). Therefore, articles reported that the crowdedness of car parks will deteriorate.

To conclude this section, it reviews the literature related to the car park crowdedness that is likely to be caused by the popularisation of EV. Investigations found that it could take up to eight hours to recharge an EV from an empty battery. When the EV charging voltage is low, it will take an even longer charging duration and leading to low parking turnover. In which, it is seen as a driver of deteriorating the crowdedness of a car park.

5.4 Consequences of adopting EV regarding electricity consumption

In Hong Kong, it has been starting the development of the EV market but not being accepted in public for various reasons. Scholars stated that one of the main public concerns in Hong Kong is about electricity transmission (Situ, 2009). The promotion of EV could increase the use of local electricity levels. "*The greater the charger rating, the larger the burden on the local electricity distribution and transmission networks*" (Mullan *et al.*, 2011, p.4350). Especially with a fast-charging network, the increase of electricity load becomes more significant. Likewise, seminal contributions have been made by Moon and other authors (2018) of their investigation in Korea. They reached a similar conclusion that the increasing diffusion rate of EV led to a larger demand for electricity nationally. By comparing and predicting the electricity demand with EV charging in a day per season, in 2030, will affect the total electricity consumption in the morning during winter which is approximately 20,000 MWh higher than the total electricity consumption at night (Ng and Moon, 2017). As the ideas drew by other literature (Qian *et al.*, 2011; Lundström and Binding, 2012), the increase of EV adoption would cost the related parties to pay extra attention to planning for the expansion of electricity transition and distribution facilities improvement.

Empirical research suggested that the peak of EV charging has an alignment with the highest period of electricity consumption. The authors stated that one of the possible reasons could be opportunistic charging, including "*charging starts simultaneously with other human activities such as early morning workplace activities and evening activities at homes*" (Fachrizal *et al.*, 2020, p.3). A similar finding was stated by Moon and other authors (2018) as well. The peak of electricity consumption of fast public and private electric vehicle supply equipment in Korea occurred during the early evening and midnight periods respectively. Furthermore, an extensive spatio-temporal study on the impacts of 16 different charging locations indicated that it is likely to occur additional electricity pressure when charging an EV (Kuang *et al.*, 2017). They discovered that it might be better to combine with solar power production if charging at non-residential buildings. It is because the building electricity energy demand will be high when building occupancy is also high during the daytime. Concomitantly, it proved that the adoption of EV imposes larger electricity consumption than before.

Moreover, recent studies have conducted an observation about EV charging load, from collecting the electricity load profile in Sweden on a day in January 2019 (Shepero and Munkhammar, 2018). It indicated that the majority of electric grids tends to have a low utilisation due to high usage in the late afternoon and low demand from midnight to morning (García Villalobos, 2016). With the increase of uncontrolled EV charging load, it was believed that the electric grids will suffer greater tensions (Fachrizal *et al.*, 2020). Some articles also elaborated further on the impacts of the increasing tension on electric grids by EV. A recent study by a group of authors (Hubka *et al.*, 2021) forecasted the electricity demand based on the past demand in the Czech Republic. They revealed that the demand due to EV broadening will incrementally add approximately 12% ten years later, and will reach to 30% increase in 2040 to the nowadays electricity production (Hubka *et al.*, 2021). They further warned that this could lead to a potential dearth of power plants in the country for supplying the electricity demand twenty years after.

In short, this section presents a review of recent literature on the impacts on electricity consumption by EV adoption, the majority of authors have investigated this field and suggested that the additional electricity demand is likely to cause an influence on the current electricity systems such as electricity load, electricity grids, power plants. When the electricity demand by EV is expected to grow exponentially, countries, where have insufficient electricity infrastructure, could suffer from the lack of electricity supply after the popularisation of EV. The literature explains that the change of using renewable energy might help to reduce emissions but cause other consequences from an urban perspective.

5.5 The constraints of the current EV infrastructure planning

Limited or no electrical infrastructure support such as charging stations is another public concern about the introduction of EV in Hong Kong amongst literature. It found that uncertainty avoidance has a negative influence on ethical attitudes, risks such as adoption barriers lead to the resistance to purchase EV (Franke and Nadler, 2008). China, for instance, a place near Hong Kong, shares numerous similarities in transport infrastructure and driver behaviour. Most of the vehicles are parked at parking slots instead of private garages due to the scarcity of land resources (Chen *et al.*, 2013). Consequently, electric vehicles chargers would be an additional load in residential or public parking lots. In which, Hong Kong is a city that suffers high density of traffic and limited parking capacity (Shao *et al.*, 2016). It demonstrates the difficulty and apprehension of the popularisation of EV in Hong Kong regarding the charging station infrastructure.

Several articles have also started to ponder the prerequisites of the implementation of EV (Tang *et al.*, 2012; Yang *et al.*, 2013). They mutually believed that the availability and accessibility of charging stations are critical towards the development of the EV market. A closer look at the literature on the specific investigation of the constraints in Hong Kong, however, reveals several gaps and shortcomings. Although the limitation of previous research on this area exists, a group of scholars indicated the potential consequences of introducing EV in a place like Hong Kong. They demonstrated that the practicability of EV is likely to be suppressed when solely expanding the number of EV in a city without sufficient deployments such as road connections, corresponding charging stations, and parking infrastructure (Lam, Leung and Chu, 2013).

The existing infrastructures might not be capable to support the expansion of the EV market, which has been discussed by a great number of authors in literature. As a similar concept that was discussed by Nunes, Figueiredo and Brito (2016), the EV charging voltage might damage the current electricity facilities (Etezadi-Amoli, Choma and Stefani, 2010). The authors explained that the existing electricity infrastructure may not be able to satisfy the surge of powering EV in charging stations in certain areas. Problems such as voltage sags and flickers could occur, leading to incremental damage to the electrical equipment in the location. Their assumptions on the locations of charging stations also lined with the discussion in Fachrizal's paper (2020), in which charging stations would be placed primarily in residential and light commercial locations. In a certain sense, the concepts from the literature summarised that it increases the difficulty for the government to restructure the existing infrastructures for EV and to identify places in building charging stations.

In summary, this section gathers the papers related to the possible constraints of the EV market. It involves two major parts which are the lack of infrastructure and the potential impact on existing infrastructures. Without a comprehensive deployment for EV, authors reported that it is likely to be detrimental for the urban.

<u>5.6 The dark sides of EV</u>

A large number of existing studies in the broader literature have examined that the expansion of EV does not always grant an absolute advantage to the urban environment.

For example, over time, an extensive literature has developed on the environmental impacts of increasing electricity usage (Baran and Legey, 2013; Ellingsen, Singh and Strømman, 2016). Concomitantly, the usage of electrical energy is likely to grow accordingly. On to the Brazilian market, it is expected to increase in electricity consumption by 31.3% in 2030 with the same speed on increasing electric vehicles (Baran and Legey, 2013). The total energy consumption was over the energy production in around 2005. There exists a considerable body of literature on the subsequent indirect pollutions of EV implementation caused by the increasing energy production. Ellingsen, Singh and Strømman (2016) indicated that EV use electricity and lithium-ion batteries which would be more environmentally friendly, contrary to conventional vehicles that rely on combustion fossil fuels propulsion. However, simultaneously, scholars (Cao, 2017) revealed that a lifecycle perspective is also indispensable for understanding the full carbon footprint of EV. Indirect emissions derived from electricity generation such as the upstream supply stage, power plant construction and decommissioning can be dramatic (Faria *et al.*, 2012; Hawkins, Gausen and Strømman, 2012).

Moreover, the production of lithium-ion batteries still causes a level of pollution. Although the use of lithium-ion batteries may be eco-friendly than the conventional source, research showed that, during lithium processing, there has the utilisation of toxic chemicals and trace amounts of lithium can be found in waste storage ponds, tailings piles, processed waters, evaporate basins and transported products (Kaunda, 2020). In which, these have biophysical consequences, leading to adversely impact human metabolism, neuronal communication, soil ecology and aquatic life.

Some papers in the past have driven the further development of the GHG emission in the EV life cycle, which was usually being ignored when considering the issues of EV (Gould and Golob, 1998). The authors discovered that, with the combination of hydroelectric power or nuclear energy, EV would provide a greater impact on ambient air quality than a standard enhancement of sulphur oxides emissions from new electricity generation. Whereas they additionally found that the impact on GHG emission is more sensitive. Recently, some literature filled the research gap in this field. A study in China (Qiao *et al.*, 2019) was reported that the GHG emission of the WTW phase of an EV dropped rapidly, but it resulted in the same pollution level during the Cradle-to-Gate phase compared to internal combustion engine vehicles. Another similar result was also found by some authors (Ellingsen, Singh and Strømman, 2016). They assessed the lifecycle of GHG emissions of four sized EV, reflecting that the increase in the size and range penalty of an EV was associated with a 1.7 increase in the lifecycle climate change potential impacts. Thus, areas with fewer green energy sources will experience a higher difference in GHG emissions between smaller and larger sized EV.

Hence, there is a wide choice of EV blemishes in the literature. Scholars believed that EV does not factually claim as a “green” vehicle. It was reflected that the additional electricity consumption by EV is likely to cause indirect emissions. Additionally, from the lifecycle of EV, some papers indicated that it could produce identical pollutions such as GHG during some phase of its production and biophysical consequences from the production of raw materials compared to traditional vehicles.

5.7 Literature research gap

All scholars mentioned above have discussed their thorough findings in terms of the areas of the research topic, meanwhile a level of interrelationship and elaboration on the content exists amongst these journal articles. Whereas their findings mostly tend to be more country-specific such as in the USA, Korea, and the Czech Republic (Oliver and Lee, 2010; Moon *et al.*, 2018; Hubka *et al.*, 2021). Although researches highlighted that the problems of parking duration and electricity transmission may be a concern with the adoption of EV, there is no paper to date has examined the impacts of electricity consumption and car park crowdedness specifically in Hong Kong. Moreover, previous research can only be considered the first steps towards a more profound understanding of the impacts of the introduction of EV. To our knowledge, no or limited prior studies have examined these problems spatially and computationally. There are only a few papers with a spatial investigation in one car park/ location (García Villalobos, 2016; Kuang *et al.*, 2017). In order to fill this research gap, this dissertation is going to use the relevant open data on these aspects published by the Hong Kong government and trying to analyse it with appropriate data analysis and visualisation.

Regarding the research hypothesis, the literature review has strengthened the assumptions made in section 3. The discussions on the potential increase of parking duration prove that the parking usage could be a factor of the impacts along with the EV popularisation. Therefore, the overall parking utilisation rate in Hong Kong from the open data can be relevant in this research. Additionally, the assumption of electricity consumption is also underpinned.

In relation to the research hypothesis, it strengthens the assumption that the car park utilisation rate is relevant to the potential impacts of EV popularisation.

6. PRESENTATION OF DATA

This section is going to describe the data used for analysing the research question. Also, the source and the key fields of the datasets will be illustrated as well as the data processing tools for the analysis and data visualisation. Finally, it will show the reproducibility of the methodology at the end of this part.

The datasets for the following analysis are divided into four different segments. Noted that the first two segments which are vehicle first registration and parking space usage, are both collected from '*The Monthly Traffic and Transport Digest'* by the Hong Kong Transportation Department. Due to the limitation of the data collection, the parking information was only recorded since January 2013. As a result, the data for this paper will be for the period between 2013 and 2020.

6.1 Vehicle first registration

The target feature of this research, EV, is extracted through the registration of vehicles by fuel type in section 4.4 from the digest. It involves the number of registered private cars which fuels by electricity, petrol, and diesel from January 2013 to December 2020. Due to the data collection of the Hong Kong Transportation department, data before 2017 was not formatted in Excel but PDF. Therefore, manual data extraction of the necessary information before that year was conducted. There are four features in the datasets, and it is processed as shown in Figure 1.

	EV	PETROL	DIESEL	period
0	292	494222	2291	201301
1	297	495909	2292	201302
2	297	498394	2296	201303
3	303	499553	2292	201304
4	304	501271	2294	201305
...	...	...	...	...
91	15878	612808	11970	202008
92	16324	615024	11971	202009
93	16417	617320	11971	202010
94	17186	618935	11970	202011
95	17998	621288	11968	202012

96 rows × 4 columns

Figure 1: A dataframe summary of the number of registered vehicles by three major fuel types in Hong Kong between 2013 to 2020

6.2 Parking slot usage

The second main dataset is about car park usage. It is collected from the section 6.1 and 6.2 from the digest. It is divided into two aspects: government multi-storey car park and public metered parking space statistics. The major difference is that public parking space data records the utilisation rate regionally, whereas the other focuses on 14 different parking locations in Hong Kong. Similarly, it captures the eight years period as above. For the convenience of data processing, both datasets are transposed to create a dataframe that the spatial elements become the columns.

```
Columns in the government multi-storey parking statistics data set:

[ Aberdeen_gov_UTL_RATE ]
[ City_Hall_gov_UTL_RATE ]
[ Kennedy_Town_gov_UTL_RATE ]
[ Kwai_Fong_gov_UTL_RATE ]
[ Middle Road ]
[ Murray Road ]
[ Rumsey_Street_gov_UTL_RATE ]
[ Shau_Kei_Wan_gov_UTL_RATE ]
[ Sheung_Fung_Street_gov_UTL_RATE ]
[ Star_Ferry_gov_UTL_RATE ]
[ Tin_Hau_gov_UTL_RATE ]
[ Tsuen_Wan_gov_UTL_RATE ]
[ Tsuen Wan Transport Complex ]
[ Yau_Ma_Tei_gov_UTL_RATE ]
[ YR_MTH ]

Columns in the public metered parking space statistics data set:

[ HK_pub_UTL_RATE ]
[ KLN_pub_UTL_RATE ]
[ NT_pub_UTL_RATE ]
[ YR_MTH ]
```

Figure 2: A column summary of the parking space usage from government multi-storey and public parking slots in Hong Kong between 2013 to 2020

6.3 Electricity consumption

The electricity consumption (terajoule) dataset is downloaded from the energy statistics report on the Hong Kong Census and Statistics Department website. Data features contain domestic (home use), commercial (workplace), industrial (manufacturing), and street lighting. The data contains information starting from 1970, and likewise, we only extracted information from 2013 for this paper.

	Domestic	Commercial	Industrial	Street lighting	Exports to the mainland of China	All groups
516	2675.0	7105.0	826.0	35.0	389.0	11030.0
517	2153.0	6435.0	776.0	32.0	158.0	9554.0
518	2408.0	7746.0	821.0	30.0	317.0	11321.0
519	2342.0	7856.0	940.0	34.0	342.0	11515.0
520	3770.0	9081.0	1023.0	30.0	475.0	14379.0
...	...	...	...	...	...	...
607	5466.0	9754.0	1047.0	29.0	0.0	16297.0
608	5774.0	9063.0	916.0	28.0	0.0	15782.0
609	4007.0	8234.0	805.0	30.0	0.0	13076.0
610	2928.0	7762.0	834.0	32.0	0.0	11557.0
611	2388.0	7384.0	816.0	32.0	0.0	10621.0

96 rows × 6 columns

Figure 3: A dataframe summary of electricity consumption in Hong Kong between 2013 to 2020

6.4 Charging stations in Hong Kong

The comprehensive charging station dataset is found from '*The Promotion of Electric Vehicles in Hong Kong'* on the Environmental Protection Department website. The dataset itself includes three voltages of EV chargers (standard, medium, and quick) in several locations from 18 districts. Since the dataset lacks the latitude and longitude of each location, we aggregated the quantity of chargers by district and manually produced a new dataframe for this study. Moreover, for the visualisation, a Hong Kong map shapefile is being utilised from Geofabrik.

All the datasets for this paper are accessible. Relevant documents are publicly available and share in the GitHub link provided on the cover sheet.

7. METHODOLOGY

In this section, it is going to mention the methodology for solving the research question. It involves five key parts: Data preparation, Descriptive Statistics, EV charging station distribution analysis, a Variance Inflation Factor (VIF) and Correlation, and Regression with Machine Learning. Datasets including the first registration of vehicle, electricity consumption, and car park utilisation rate will be processed through Python with independent python notebooks. For producing the EV charging station map in Hong Kong, RStudio will be the tool for data munging and visualisation.

Since all datasets in this research are publicly available, after consulting with the supervisor, there is no need to have an ethics application.

7.1 Data preparation

Firstly, data cleaning and data wrangling are the prerequisites. It will start with converting into a useable dataframe such as removing NaN fields, dealing with a data type, and merging datasets. For instance, in the first registration of vehicle datasets after 2017, there is a blank separating the number of registered petrol cars (Figure 4). It is required to remove the space and convert it into an integer for further data processing.

Furthermore, the features of some original datasets might not be useful for the research. Loading high dimensional data could decelerate the operations of the virtual machine. Therefore, a manual feature engineering is going to be in place. For example, we only extract three main fuel types of private vehicles out of numerous varieties. Another example is that, as mentioned in the section above, the rows and columns of the parking usage are going to be transposed. The detailed procedures and results of the data cleaning and wrangling will not be displaced in the later section but they can be found in the Python notebooks shared in GitHub.

	Unnamed: 0	Unnamed: 1	Unnamed: 2	Unnamed: 3	Petrol
0	NaN	NaN	NaN	NaN	Registered
1	電單車 (無邊卡)\nMotor Cycles (Solo)	NaN	NaN	NaN	84 954
2	電單車 (連邊卡)\nMotor Cycles (Combo)	NaN	NaN	NaN	113

Figure 4: The literal problem in the raw registered vehicles dataset

7.2 Descriptive Statistics

Secondly, descriptive statistics of the key features will be performed. This step is to provide a mathematical understanding of the distribution of the data. In light of the focus of the research question, the number of first registered electric vehicles would be the respondent. Information such as average value, minimum and maximum, and interquartile range would help to determine the magnitude of the data when comparing to another period. For the visualisation method, we believe that histogram is regarded as the most appropriate tool to present the frequency of the data. In order to outline the key statistical values and the shape of the data, dash lines and a line curve will be added to the chart. When observing the distribution of the data, it is essential to look at the outlines as well. A boxplot visualisation will be adopted alongst with the histogram.

7.3 EV charging station distribution analysis

Thirdly, it is then going to conduct a spatial EV charging station distribution analysis. This step is for visualising the location of the current and planned charging stations in Hong Kong. As mentioned in section 6, we aggregated the number of chargers by district regardless of their charging voltages. It is expected to reveal some insights into the distribution pattern of the charging station such as the most concentrated areas. It is expected to discover urban planning issues such as resource mismatch from this result.

7.4 Variance Inflation Factor and Correlation

Fourthly, to implement a VIF and Correlation of the datasets for observing the impacts of each variable towards the number of first registered EV. Before VIF, a correlation matrix will be produced for indicating the level of correlation amongst features.

VIF is to measure the level of multicollinearity in a set of multiple regression variables. This process involves calculating VIF on each feature in a dataframe and repeatedly drop the columns with the highest VIF for avoiding highly correlated features. If two independent variables are closely related, the results produced from the regression model are likely to be double counted. We will set a VIF threshold of 6 which was tested in line with the most reasonable coefficient of determination and meaningful outcomes by trial and error. The filtered features (VIF) will then proceed to conduct a linear regression with the response (the number of first registered EV). Four types of electricity consumption are prearranged to not be excluded, and group into a list parameter '*list_var_not_to_remove*'. The rationale is that it represents four categories of electricity usage, it could be highly correlated between categorical variables. Therefore, these variables should not be removed even though it has a high VIF. Ultimately, we are going to interpret the most significant coefficient values for each variable in the correlation model.

7.5 Regression with Machine Learning

Finally, a regression with machine learning on the most dramatic coefficient variable will be performed. There is a large amount of the data for those monthly data over eight years (almost a hundred rows). By using machine learning techniques, it would lower the vulnerability of the model that inputting unseen data for future studies will significantly alter the relationship pattern between variables. For the target and response, it will first standardise with '*preprocessing.scale*' from Scikit-learn. It is to divide the data points by the standard deviation and subtract the mean for each data point. Standardisation would be a helpful pre-processing technique, especially for machine learning, to compare two data since each feature after standardisation will have internally consistent content and format. As the number of first registered EV and the car park utilisation rate do not measure in the same unit, which do not contribute equally to the analysis and might end up creating a bias if not standardised.

In light of the result of the VIF and correlation regression, we will select the variable with the highest coefficient and conduct a single regression with the number of first registered EV. Furthermore, it is going to compare the performance from different models, including the linear model, polynomial, and improved polynomial models. The Root Mean Squared Error (RMSE) will be the determination of the model fitness. A line chart will be produced for visualising the comparison, tested by splitting 20% of the data into training set size. After, the polynomial model will be improved by adopting either Ridge or Lasso optimisation. A model overview will be performed respectively and then we will select which optimisation to use depending on its compatibility. From the comparison of those three models, we will discuss the RSME on each model and choose the most accurate and appropriate regression model for proceeding to the interpretation of the variables.

Eventually, after all these five methods, it is expected to come with some key insights to the research question and fill the academic gap towards the study around the Hong Kong electric vehicles situation.

8. RESEARCH LIMITATIONS

This research shares several similar limitations the same as other studies. It can be divided into methodology-related/ data-related.

Starting with the constraints of the methodology approach, some fields such as the VIF threshold and the proportion of test set are defined subjectively or based on trial and error. It could lead to the situation that the results could have various conclusions depending on the choice of hyper-/parameters. For instance, in the VIF, we attempted that a threshold at 6 is more able to provide a clear outcome for discussion. It is the same situation when deciding the level of degree for the polynomial regression model. However, due to the requirement of hardware and time pressure, it is difficult to test the optimal minimum but local minimum.

Another issue is about the assumption and availability of the datasets. As discussed in the previous sections, due to the lack of open datasets, this research needs to assume that parking slots are or will be used for EV charging. Another reason for underpinning this assumption is the direction of the Hong Kong EV roadmap policy. The government is aiming to expand the charging network by mainly installing chargers in new/ existing commercial and government-owned car parks (Environment Bureau, 2021). The usage would be an indication to observe the potential busyness of a car park by EV. As a result, the datasets about government and public parking usage collected from the Hong Kong government institution will be relevant for this EV study.

Also, we need to assume that the electricity consumption is partially affected by EV charging. Since we are not able to collect the electricity use by EV specifically, this assumption has to be made if the only source is the general figure offering publicly. Consequently, this assumption is likely to have a pitfall of causation. But if the electricity consumption by EV impacts dramatically, the aggregated electricity consumption would be able to reflect the trend.

Besides, some datasets contain a short period of information only. For example, the first registration of vehicles dataset keeps data since 2013 but all other datasets in this research can be chased back to 1970. Due to the incoherent number of rows, it is restricted to investigate data from 2013. In which, it could affect the depth of the research and lower the effectiveness of machine learning on predicting data.

Despite the limitations of this research, the available datasets and the methodology of this paper will still grant a reasonable level of confidence for concluding. Procedures such as minimising the RMSE, maximising R2 value, and processing about a hundred data points would ensure the accuracy of the model and the statistical significance of the outcome. Thus, we believe that, by using the publicly available datasets, we can still reach a relatively factual and reliable unambiguous conclusion on this research question with limited resources.

9. RESULTS

For the following paragraphs, it is going to solely illustrate the results of the data processing in connection with the research objectives. It will be ordered by the flow of the methodology. The implications will mention separately in section 10 (Discussion).

Figure 5 demonstrates the data distribution of the number of first registered EV over the past eight years in Hong Kong. The mean amongst data points is around 7,080. The lowest monthly number of first registered EV is 292 and the peak could reach about 18,000. It shows a bimodal shape in the data distribution since there are two peaks at different intervals. By observing two peaks separately, both appear a highly positive skewed pattern. The number of first registration in EV is concentrated in the range of 0 to 2,500 and 10,000 to 12,500. From the boxplot, it shows that the majority of data points is ranged much above the minimum which is indicated by the long interquartile range located near the top.

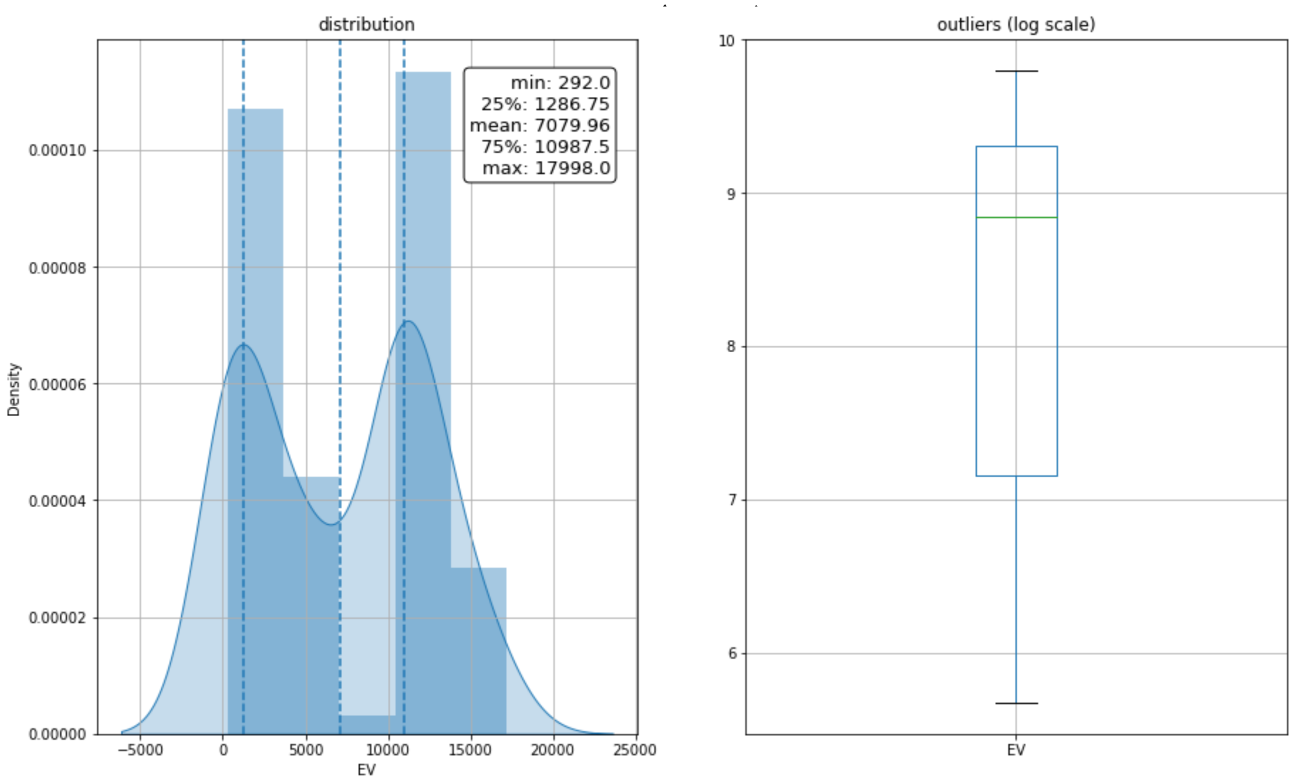

Figure 5: Descriptive statistics on the number of first registered electric vehicles

The line chart below presents a gradually increasing trend of registered EV in Hong Kong between 2013 and 2020. It was a steady rise in 2013 and 2014. Starting from around January 2015, it occurs an exponential increase. Most significantly, there was a surge with approximately 3,000 registered EV more concentrating during the first period of 2017. After, it kept climbing to about 17,500 registered EV in December 2020.

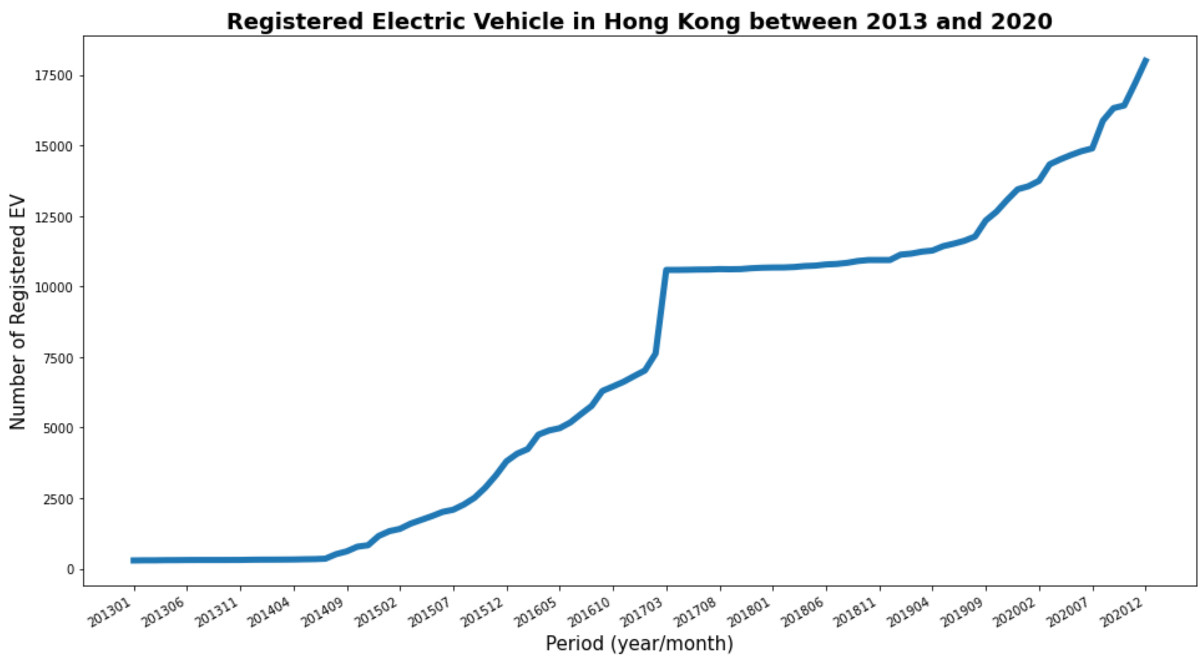

Figure 6: The increasing trend of first registered EV in Hong Kong in the past eight years

The following figure visualises the distribution of EV charging by the districts in Hong Kong up to 2020. The district with the highest number of EV chargers is in Kwun Tong, with almost 830 EV chargers in that area. It is remarkably high, especially when comparing to a district like the southern part of Hong Kong Island with only 55 chargers. The central and western district, Wan Chai, Sham Shui Po, and Yau Tsim Mong district all recorded more than 200 EV chargers in 2020. And the remaining districts have around 100 EV chargers on average.

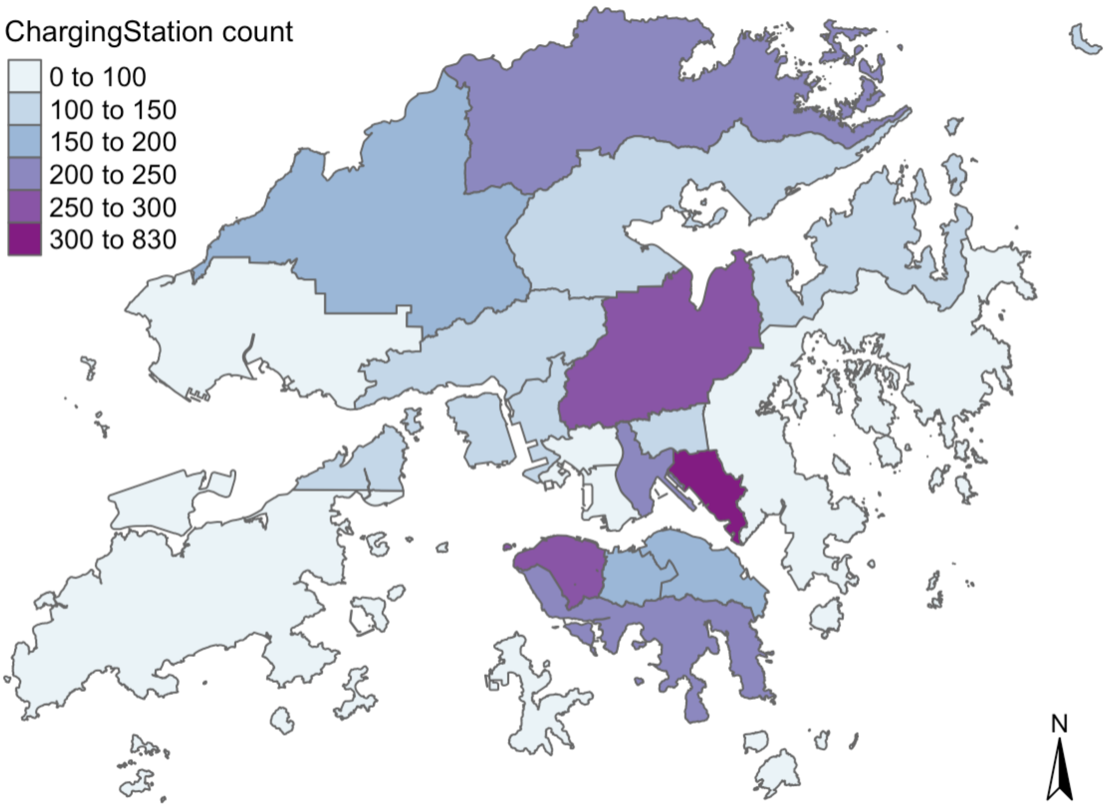

Figure 7: The distribution of EV chargers in Hong Kong

The correlation matrix in Figure 8 was about the impact of the number of registered EV in Hong Kong against 21 features, ranging from highly correlated (1) to uncorrelated (-1). Amongst features, the types of registered vehicles, the electricity consumption, and government/ public parking utilisation attribute a unique form. Vehicle types are highly correlated, four areas of electricity consumption are in the middle of the range, government-owned car park usages are mostly positively correlated and public parking usages are predominantly negatively correlated.

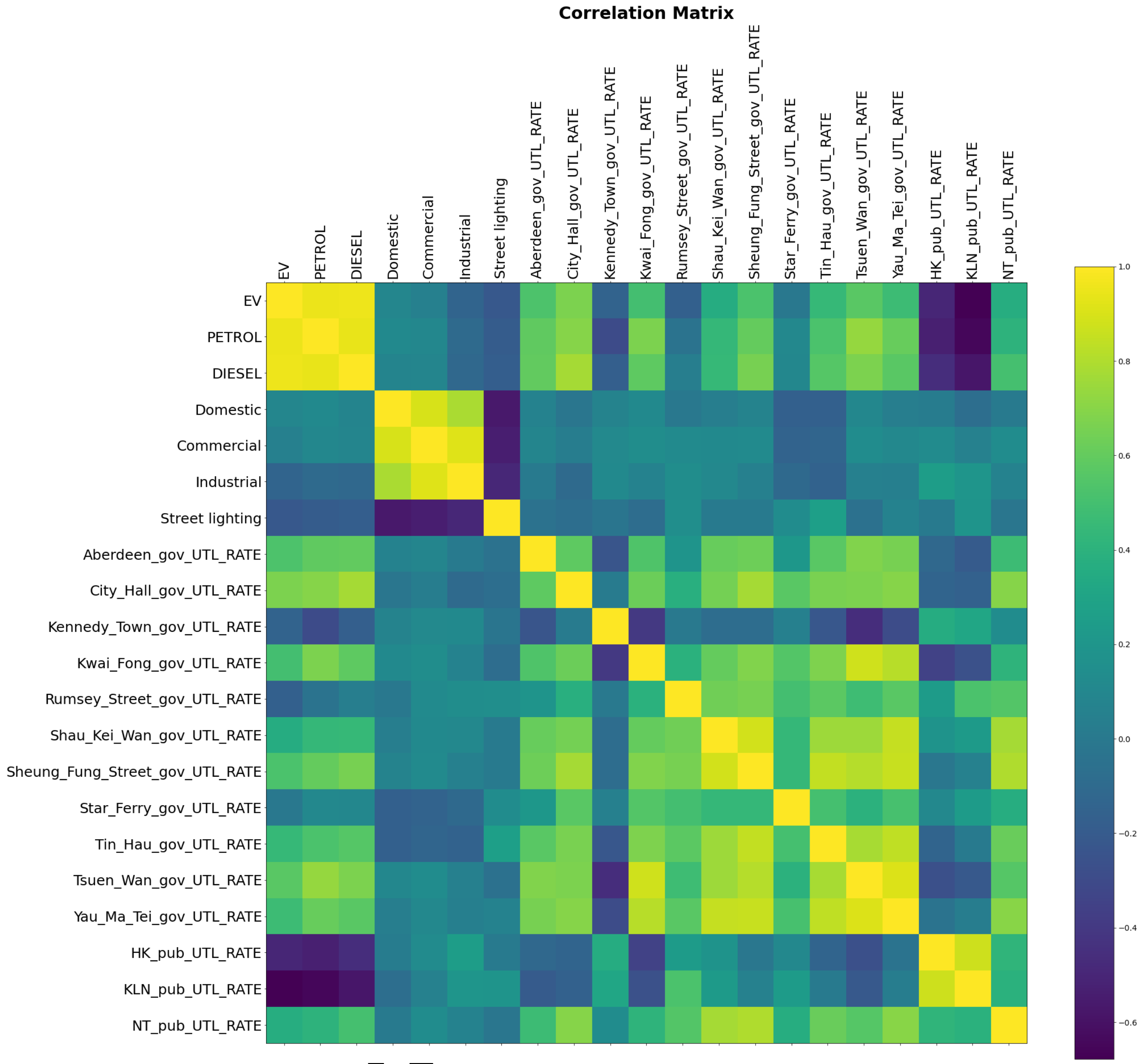

Figure 8: Correlation matrix

Figure 9 demonstrates a summary of the outcome after implementing VIF between 21 variables. The initial VIF of all features is around 73. In the wake of removing eight multicollinear columns, it reached the preordained threshold of about 5.4. Ultimately, only 13 columns have remained for further analysis.

```
Max VIF: 73.12346946933478
Dropping: DIESEL
Max VIF: 55.35518095683232
Dropping: KLN_pub_UTL_RATE
Max VIF: 37.210078174482774
Dropping: PETROL
Max VIF: 19.82437383335386
Dropping: Sheung_Fung_Street_gov_UTL_RATE
Max VIF: 17.922031058598485
Dropping: Tsuen_Wan_gov_UTL_RATE
Max VIF: 12.667427519413678
Dropping: EV
Max VIF: 11.643316434780159
Dropping: Yau_Ma_Tei_gov_UTL_RATE
Max VIF: 10.438389955891937
Dropping: NT_pub_UTL_RATE
Max VIF: 5.435580106315374
The columns remaining after VIF selection are:
Index(['Domestic', 'Commercial', 'Industrial', 'Street lighting',
       'Aberdeen_gov_UTL_RATE', 'City_Hall_gov_UTL_RATE',
       'Kennedy_Town_gov_UTL_RATE', 'Kwai_Fong_gov_UTL_RATE',
       'Rumsey_Street_gov_UTL_RATE', 'Shau_Kei_Wan_gov_UTL_RATE',
       'Star_Ferry_gov_UTL_RATE', 'Tin_Hau_gov_UTL_RATE', 'HK_pub_UTL_RATE'],
      dtype='object')
```

Figure 9: The process of VIF and the remaining columns after VIF selection

Following VIF, Figure 10 presents the Ordinary Least Squares (OLS) results in the linear regression. The model has explained most of the variation (91%) in the number of first registered EV around its mean. Also, the adjusted R square value shows that 89.7% of the variation is explained by only the independent variables that affect the dependent variable. The kurtosis value is ranged at 3.521, indicating that there are more data in the tails of the dataset rather than around the mean as it has heavier tails than a normal distribution. Regarding the coefficient value, with an increase of the dependent variable, City_Hall_gov_UTL_RATE and Tin_Hau_gov_UTL_RATE are being affected positively the most with 342 and 320 coefficient values respectively. Meanwhile, the largest negative coefficient value is Rumsey_Street_gov_UTL_RATE with about -340. There are a couple of variables resulting in approximately -270 coefficient values, including Star_Ferry_gov_UTL_RATE, HK_pub_UTL_RATE, and Street lighting.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                     EV   R-squared:                       0.911
Model:                            OLS   Adj. R-squared:                  0.897
Method:                 Least Squares   F-statistic:                     64.58
Date:                Wed, 28 Jul 2021   Prob (F-statistic):           1.97e-37
Time:                        11:13:08   Log-Likelihood:                -845.43
No. Observations:                  96   AIC:                             1719.
Df Residuals:                      82   BIC:                             1755.
Df Model:                          13
Covariance Type:            nonrobust
================================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------
const                      7047.0383   7676.001      0.918      0.361   -8222.974    2.23e+04
Domestic                     -0.1739      0.400     -0.435      0.665      -0.969       0.621
Commercial                    1.0339      0.622      1.662      0.100      -0.204       2.271
Industrial                  -13.0524      5.483     -2.380      0.020     -23.960      -2.145
Street lighting            -264.1438     97.236     -2.717      0.008    -457.577     -70.711
Aberdeen_gov_UTL_RATE       -99.7077     73.458     -1.357      0.178    -245.840      46.424
City_Hall_gov_UTL_RATE      341.6711     37.170      9.192      0.000     267.729     415.613
Kennedy_Town_gov_UTL_RATE    86.3247     48.549      1.778      0.079     -10.254     182.903
Kwai_Fong_gov_UTL_RATE       66.6961     27.939      2.387      0.019      11.118     122.275
Rumsey_Street_gov_UTL_RATE -339.9357     37.912     -8.966      0.000    -415.356    -264.516
Shau_Kei_Wan_gov_UTL_RATE   231.9339    106.201      2.184      0.032      20.666     443.202
Star_Ferry_gov_UTL_RATE    -276.2718     41.707     -6.624      0.000    -359.240    -193.303
Tin_Hau_gov_UTL_RATE        320.3433     71.339      4.490      0.000     178.428     462.258
HK_pub_UTL_RATE            -272.7598     78.259     -3.485      0.001    -428.443    -117.077
==============================================================================
Omnibus:                        6.685   Durbin-Watson:                   1.358
Prob(Omnibus):                  0.035   Jarque-Bera (JB):                6.087
Skew:                          -0.559   Prob(JB):                       0.0477
Kurtosis:                       3.521   Cond. No.                     4.11e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.11e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Figure 10: A summary result of the regression model

Sequentially, the graphs below will express the relationship between the number of registered EV and the feature with the most significant coefficient value (City_Hall_gov_UTL_RATE).

Figure 11 illustrates the data distribution after standardisation. Besides several outliers in the lower-left corner of the graph, the distribution appears an S-shape over the data range.

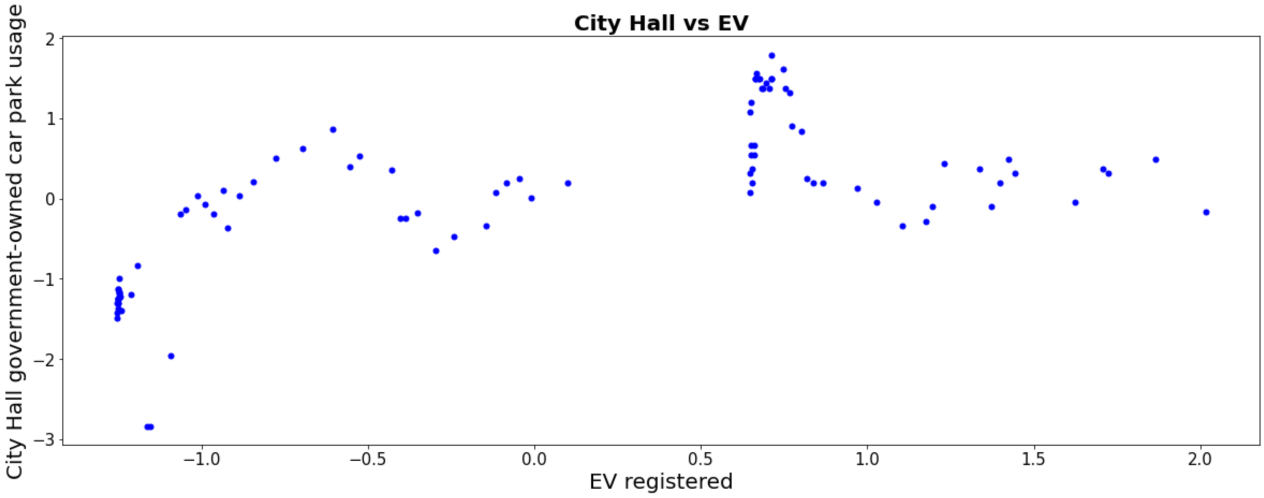

Figure 11: The data distribution between City Hall government-owned car park utilisation rate and the number of first registered EV

The linear model is able to provide a generally straight line curve summarising the data distribution (Figure 12).

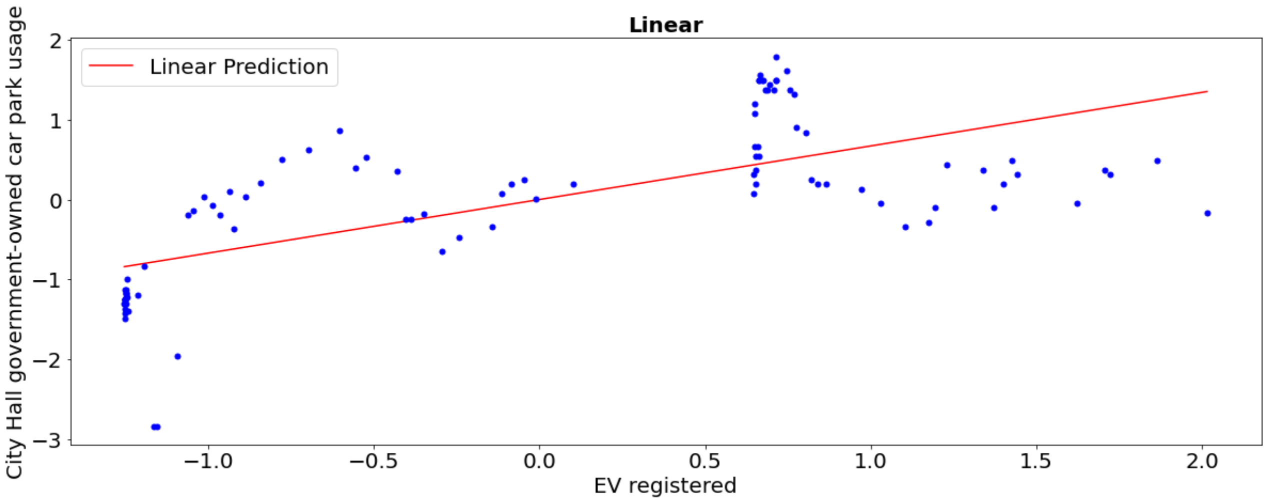

Figure 12: Linear regression model

For Figure 13a and 13b, it shows the RMSE performance on linear and polynomial regression models after splitting the dataset into training and validation set.

In the linear model, the RMSE varies from 0 to 4. After around 3 training set sizes, it remains constant at nearly 1 RMSE and eventually, the training set has higher RSME than the validation set since about 54 training set sizes.

The RMSE has appreciably reduced to the range between 0 to 1.4. It keeps consistent at approximately 0.5 RMSE after 20 training set sizes. And similarly, the RMSE of the training set is larger than the validation set along with the increase in training set size.

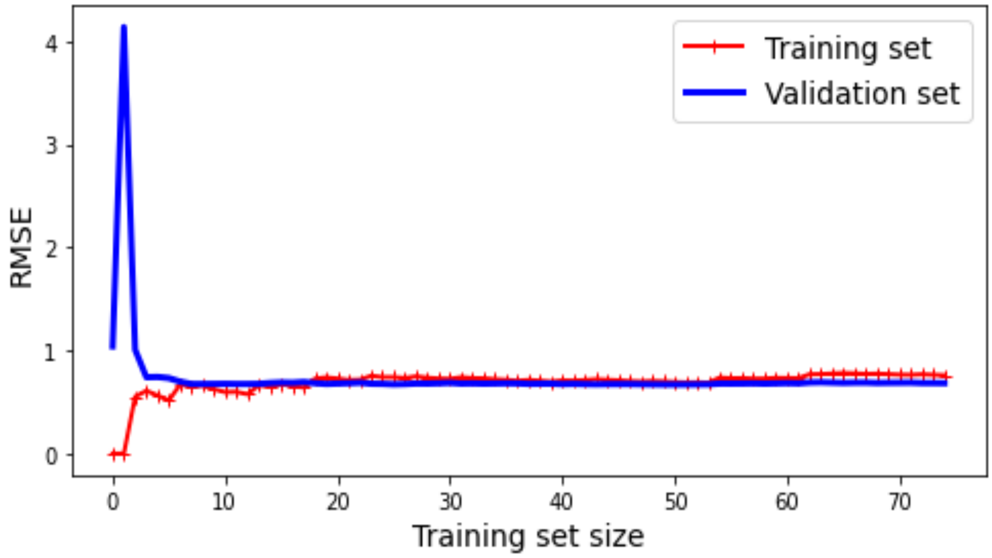

Figure 13a: RMSE performance over different training set sizes on the linear regression model

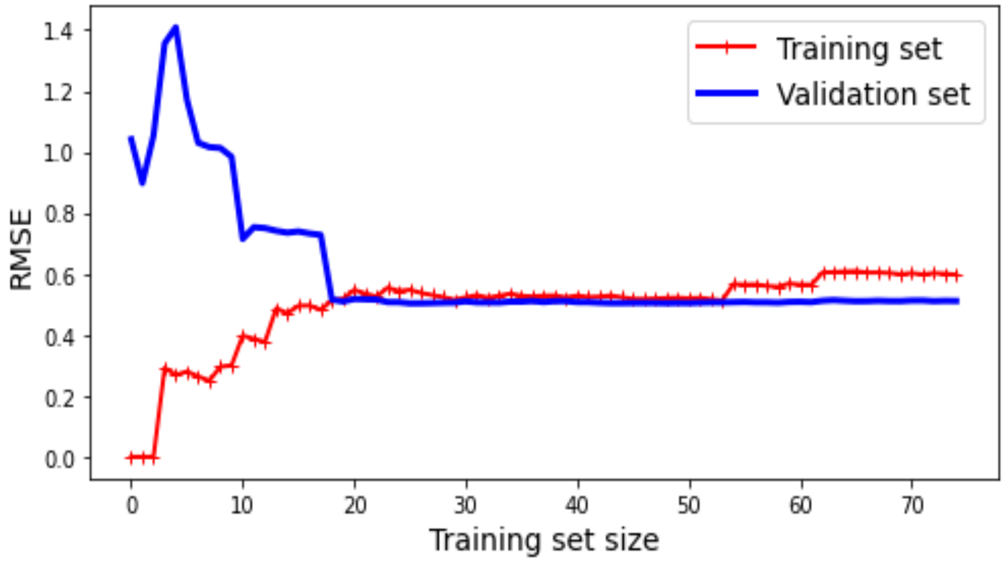

Figure 13b: RMSE performance over different training set sizes on the polynomial regression model

Figure 14 demonstrates the prediction line of the polynomial regression model with a degree of 20. Most of the data points are being represented except for some extreme values.

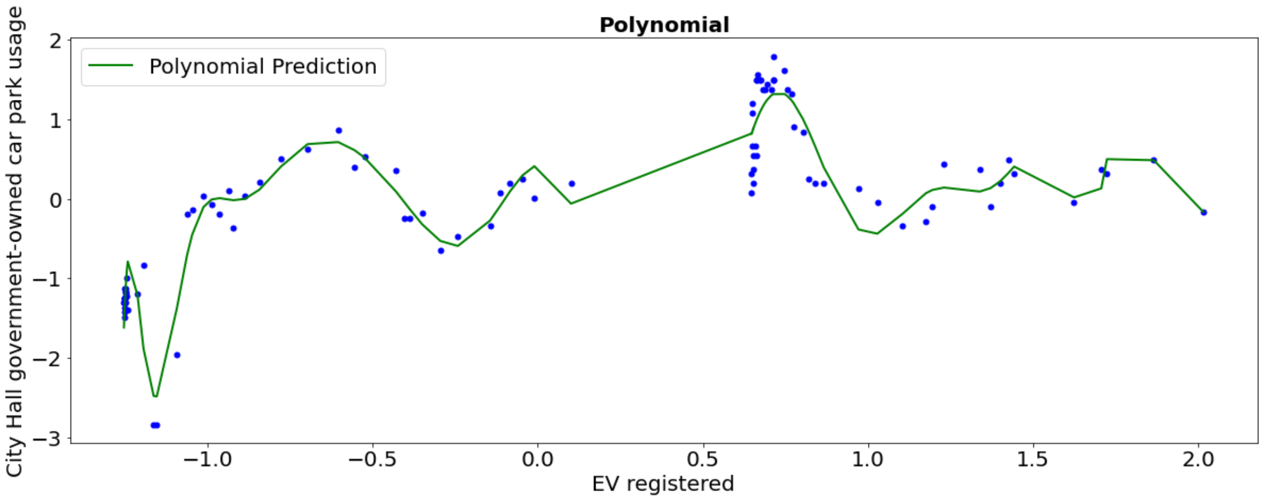

Figure 14: Polynomial regression model

Figures 15a and 15b display different outcomes of the model optimisation with Ridge or Lasso under several hyperparameters. The left sub-graph shows the results with the linear model and the polynomial model is on the right. With the rise of hyperparameters on each optimisation method, the prediction line will become flat eventually. And with a slight increase of the hyperparameter, the curve will be marginally less overfitted with the raw data points.

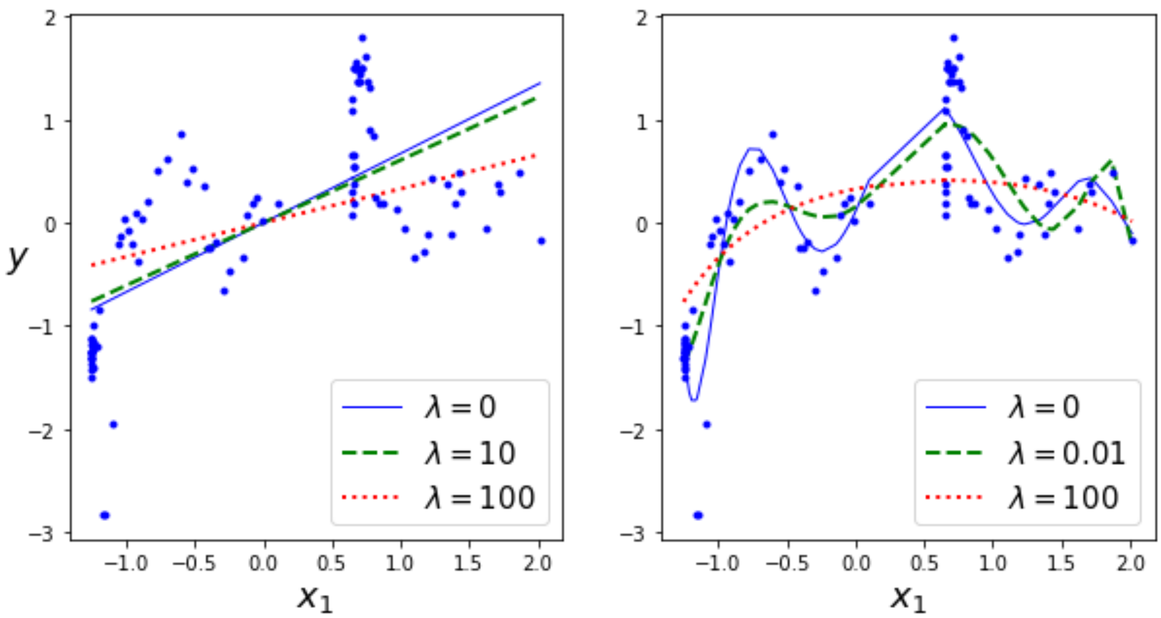

Figure 15a: Model optimisation with Ridge

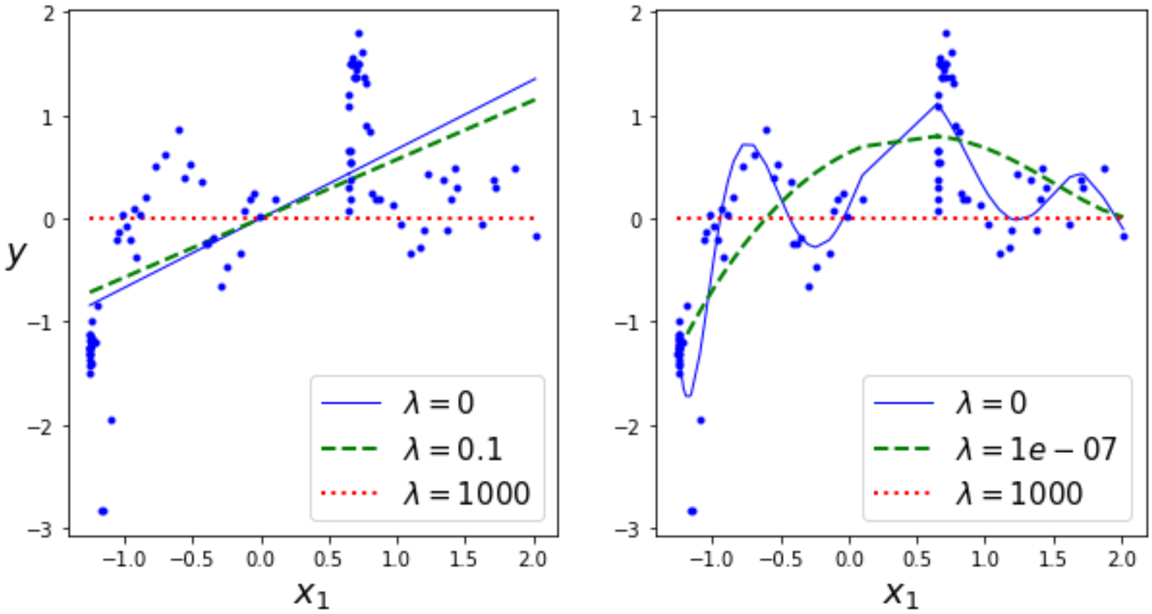

Figure 15b: Model optimisation with Lasso

Figure 16 shows the prediction curve after adopting Ridge in the polynomial regression model. Unlike the original polynomial model, this model illustrates an ordinary summary of the data distribution with a relatively dynamic prediction.

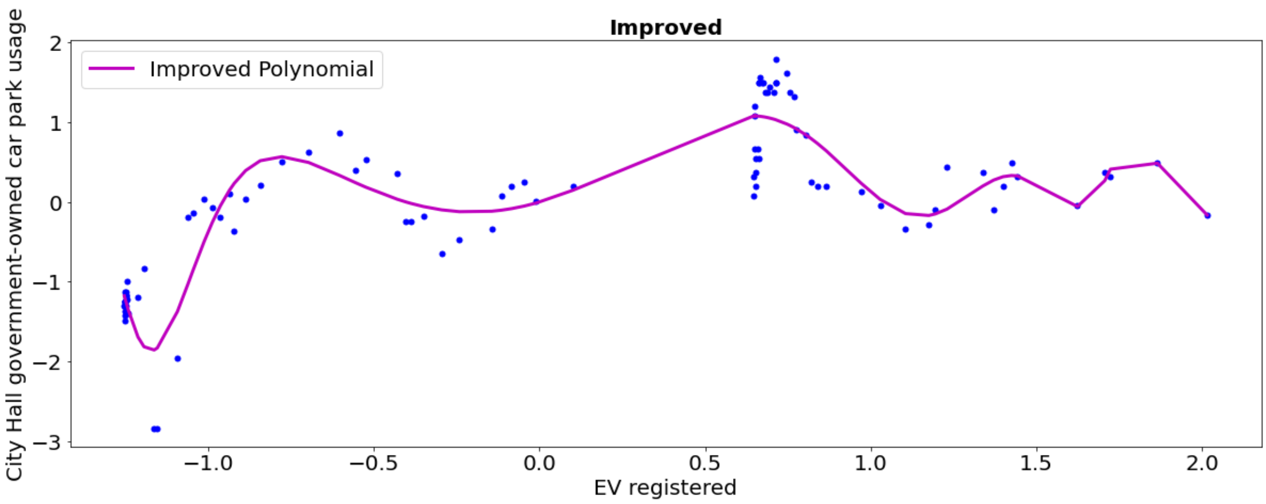

Figure 16: Improved polynomial regression model (with Ridge)

Figure 17 displays the comparison between polynomial and improved polynomial models in the same graph. It is clear to see that both models perform outstandingly in describing the data trend, but it has a slight difference between the two in terms of the fitness of the original data.

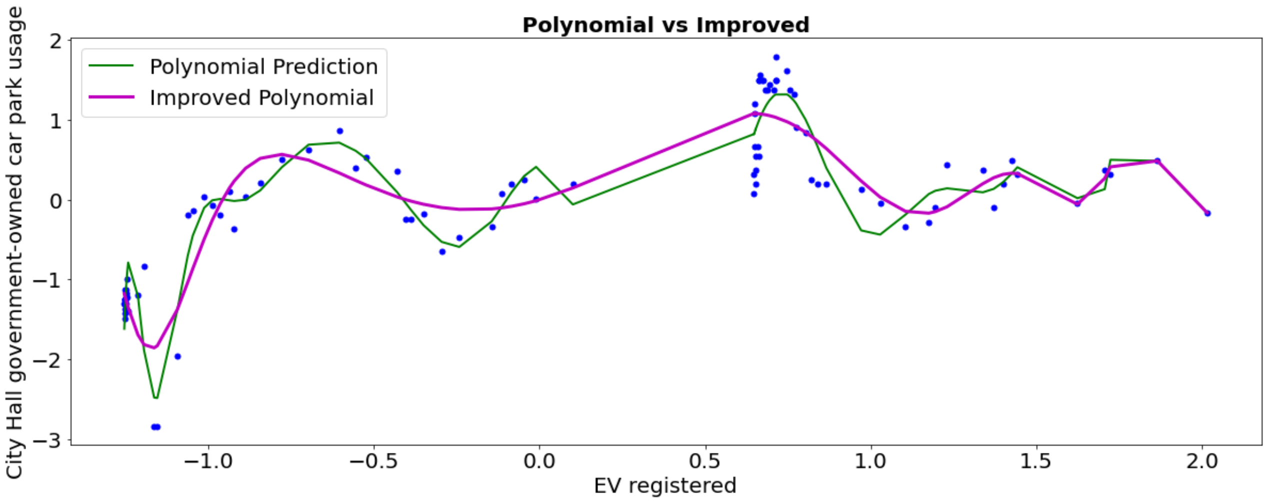

Figure 17: Model performance between polynomial and improved polynomial

Finally, Figure 18 gathers the prediction line of all three models in one chart, regarding the relationship between the number of registered EV and parking utilisation rate in City Hall.

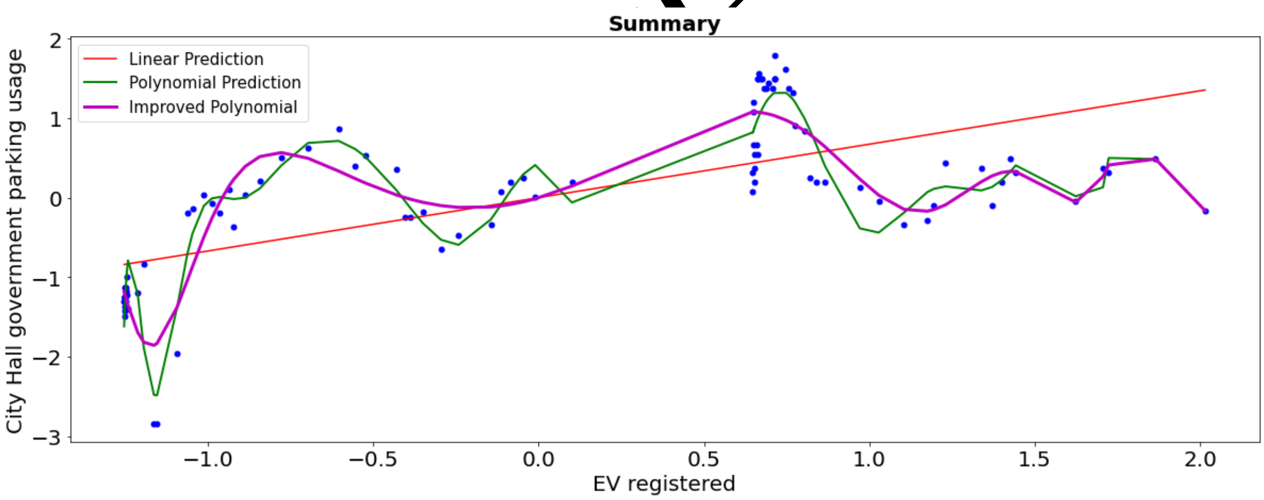

Figure 18: Model performance overview

The highest root mean square is found from the linear model, with around 0.78 RMS (Figure 19). Rather, the polynomial model predicts well with these two variables. This method is able to reduce about 0.4 RMS. On the other hand, the ridge model has a slightly larger RMS than the normal polynomial regression model.

```
rms_lin = 0.7843
rms_poly = 0.3063
rms_poly_improved = 0.4047
```

Figure 19: RMS on each regression model

10. DISCUSSIONS

This section is going to interpret the context and meaning of the results displayed in the previous section. It will relate to the research objectives and the structure of the later paragraphs will be followed by:

1) The situation of the previous and current EV charging station in Hong Kong
2) The impacts of car park crowdedness
3) The impacts of electricity consumption

10.1 The previous/ current situations of EV in Hong Kong

The EV demand is exploding as the number of first registered EV increased sharply over the period in Hong Kong. Throughout the eight years observation, the peak of EV registration was about 17,800 higher than the lowest monthly number (Figure 5). There are three main moments in the overall registration trend, where are before 2014, around the fourth quarter of 2014, and in the first of 2017.

10.1.1 Failures in the previous years

First and foremost, the insufficient amount and inappropriate location for building charging stations could be the factor of the failure in promoting EV market before 2014. As shown in Figure 6, the number of registered EV was relatively softened at the beginning of the period. In fact, the EV infrastructure has been implemented and consummated by both government and commercial parties during that period. Despite some of the biggest electricity providers such as CLP Power agreed to extend free charging services for the EV popularisation (CLP, 2012), it did not attract a substantial amount of Hong Kong drivers to switch to low-carbon driving from the figure.

One of the major reasons is the convenience of EV infrastructure. According to the CLP media press (CLP, 2012), they offered around 140 charging points across districts such as Kowloon, New Territories, and Lantau Island. But the main constraint of these charging locations is about the location of the charging stations. Although there were around 140 charging points provided by CLP, some of the chargers were built in relatively inconvenient places. Installing fast-charging stations in the countryside such as Hong Kong Science Park (the northeast of Hong Kong) and Hong Kong International Airport (an isolated island in the west of Hong Kong) is unlikely to promote the EV market. It can be referred back to the several papers that vehicles mostly park in workplaces or being driven during the daytime (Freund, Lützenberger and Albayrak, 2012; Galus *et al.*, 2013). Locations such as Hong Kong Science Park, has been suffering from low crowdedness and staff exiting problem in the area (Kao, 2017). Although these locations are able to provide plenty of spaces for building charging stations, the decision of building a charging station (especially installing a quick-charging station) in these areas could be inappropriate. On the other hand, it would happen the same in the airport, where usually appears high crowdedness. If the parking spaces are nearly full in Car Park 4, according to the airport website (Hong Kong International Airport, 2021), drivers are required to divert to other car parks for parking. Importantly, all chargers are installed in Car Park 4. As a consequence, it raises inconvenience to EV drivers during peak time in the Hong Kong airport. In summary, inconvenience is seen to be less attractive for cultivating EV driving in line with the driving habit found by literature.

10.1.2 The boost in 2014

Whereas until the fourth quarter of 2014, the increase of registered EV could be due to two main factors. The first juncture is likely to cause by the introduction of Tesla. As stated in the introduction section, Tesla is now the biggest EV manufacturer with the highest market cap and car sales in the world. Therefore, its company value and impacts on car drivers should be taken into account when assessing the introduction of the EV market. In accordance with the Tesla press, Tesla Model S was first available in Hong Kong in 2013, in which Hong Kong was the first place in Asia where consumers could drive Model S on roads in advance (Doi, 2013). The first Tesla Model S arrived in around July 2014 (The Tesla Motors Team, 2014). By considering the delivery time of the rest of the orders, it can explain the increasing trend starting from the fourth quarter of 2014 (about September 2014).

10.1.3 Economic incentives towards the use of EV

The second reason could be linked to the economic factor (government tax). The tax benefit and incentives are critical in the initial stage of EV popularisation. In line with Fachrizal's argument (2020), the higher number of EV popularised comes with the lower overall costs of EV. In light of the budget speech of the Hong Kong government in 2009, the financial secretary agreed to extend the exemption for EV from the first registration tax to further promote the use of EV (Tsang, 2009). However, the incentives were about to end in March 2017 due to the purposes of curbing car growth and improve traffic (Cheng, 2017). Such a government decision can explain the blockage of rapid growth in EV first registration in the first of 2017 (Figure 6). Up to the later years, an increase was appeared due to the following expansion of EV infrastructure. Incidentally, a rapid increase will be expected to see. While the first registration tax was HK$97,500 in 2017, a higher concession of the tax rose to HK$278,500 in 2021 under the "One-for-One Replacement" (Legislative Council Secretariat, 2021) scheme. Additionally, with the corresponding policy of the EV popularisation roadmap, it will have more incentives and facilities for boosting the use of EV.

<u>10.2 The distribution of EV charging stations in Hong Kong</u>

After the discussion on the trend of the EV first registration, it is going to interpret the charging station pattern in Hong Kong. By observing Figure 7, the problem of the resource allocation of EV chargers is clearly demonstrated.

<u>10.2.1 Excessive charging stations in the busiest districts might not be necessary</u>

More than 250 charging stations are recorded in the areas of Yau Tsim Mong district and Central and Western district, and Kwun Tong district recorded up to around 800 chargers. All three districts share the similarity of high-density location. The land population density of Kwun Tong was around 58,000 people per square kilometre, meanwhile Mong Kok (part of the Yau Tsim Mong area) was rated as the most densely populated place on Earth (Information Services Department, 2015; Keegan, 2017). Central and Western district is the core financial area in Hong Kong as an international financial centre. As Galus's paper (2013) indicated that workplaces are usually parked longer than other areas, it is reasonable to place charging stations in busy locations like these districts. Yet, it raises the doubt of the necessity of building numerous charging stations in a small area. For example, the area of Kwun Tong has around 1,100 hectares (Kwun Tong District Council, 2015). A location where is equivalent to approximately 1,100 rugby fields, installed up to 827 EV chargers in total (proportion 1:0.75). Considering the non-parking and green areas, from an infrastructure planning perspective, it could be excessive for having a great number of chargers in a location. An appropriate infrastructure planning would contribute largely to the convenience of EV driving, especially when Hong Kong is still in the initial stage of EV popularisation.

10.2.2 Inappropriate location for charging stations

Charging stations should not be installed by space availability rather than the demand. Though Hong Kong is naturally disadvantageous in land resources, there were around 76% non-built-up land until 2015 (Legislative Council Secretariat, 2016). In which, Northern and Southern districts had up to 1,419 and 424 hectares of available land for development. It provides adequate areas for building a charging station. However, these two districts are in the most northern and southern of Hong Kong. Considering the convenience of the use of charging stations, it is unlikely and unjustifiable to satisfy the EV charging demand in other districts by requiring drivers to recharge EV in an extremely away place.

10.3 The impacts of car park crowdedness

It is found that there is a strong correlation between the number of first register EV and parking usage. The correlation matrix (Figure 8) shows that an increase of EV first registration has a positive correlation with most government multi-storey car park utilisation rates. The boost of government-owned car park usage could be due to the continuous investment in EV infrastructure. According to the Environmental Protection Department's (EPD) announcement (Environmental Protection Department, 2016, 2017), they upgraded around 200 EV standard chargers to medium chargers at seven government-owned car parks in recent years. Since literature has revealed that charger voltage would affect charging duration, the upgrade could attract more drivers to park in government-owned car parks. It can explain the possible reason for the correlation between the number of first registered EV and government-owned car park usage.

Yet, along with the attractiveness, the negative impacts of car park crowdedness are being appeared. For example, the government-owned car park in City Hall has the highest coefficient value in the OLS regression model. The EV first registration number rises by 1 unit results in an incremental increase of utilisation rate by 342. Before looking at the interpretation, it is going to first comment on the effectiveness of the regression model with machine learning.

10.3.1 Machine learning – Model explanations

In order to achieve the final research objective, a regression model between the number of first registered EV and "City_Hall_gov_UTL_RATE" with machine learning techniques was produced. This sub-section is solely discussing the mathematical meaning of the model results, and its implications will cover in the next section.

At first, the linear prediction (Figure 12) gives a rough overview that the more EV registered comes with the more parking utilisation rate in City Hall government-owned car park. The model contains a large gap between the predicted points and actual points, indicating substantial biases in the model. Consequently, a high bias situation could lead to a potential underfitting issue, where high regularisation may only be able to provide a general overview and trend of the data.

By investigating the RMSE with different training set sizes, the linear model suffers a high RMSE during a small training set size (Figure 13a). It could lead to the inaccurate of the model since the predicted points cannot correctly fit with the actual data points. On the other hand, when the polynomial degree increases to 2, the RMSE drops significantly up to 1.4 and eventually maintains at around 0.5 over training set sizes (Figure 13b). It indicates that this dataset has a better fit with the polynomial model. Therefore, the remarkable drop implies that this data shows greater compatibility in the polynomial model. For reaching high accuracy, the degree of polynomial would be the direction in terms of optimisation. However, both models appear a slight underfitting problem when the training set size increased. When the training set size was near 20, the RMSE of the training set will become larger than the validation set. It indicates that the results in the training set might not reveal the actual performance in the validation set. Thus, in practice, the model will train well in the sample, but only has insignificant predictive value when trained out of sample. But in this case, it is regarded as acceptable since the gap of both sets is just around 0.1 differences.

But the relatively low RMSE of the polynomial model reveals a high level of noises, which could lead to an overfitting issue. The curve of the model (Figure 14) is influenced remarkably by the outliers. When unseen data is added, the prediction line is likely to be reshaped resulting in an inaccurate model prediction under the current dataset.

Hence, the deficiencies of both models bring to the use of optimisation methods (Lasso and Ridge) for better prediction. In the plots (Figure 15a and b), the change in hyperparameter influences the fitness of the prediction line. Lower value means fewer penalties applied on the OLS part of the formula and vice versa. Lasso is generally adopted when there are many features (because it automatically does feature selection), Ridge reduces the model complexity by coefficient shrinkage through L2 regularisation techniques. Thus, Ridge will be a better optimisation tool for this dataset.

We can see that the improved polynomial model can better describe the data trend while not being affected by the outliers (Figure 17). After the optimisation, the model is now capable to input more unseen data for relevant studies in the future and maintain a high level of accuracy. The RMS is now improved from under- and overfitting problems, by about 0.3 compared to the linear and polynomial model without Ridge (Figure 19).

<u>10.3.2 Regression - Interpretation</u>

The increase of the registered EV could be in line with the busyness of City Hall parking usage although the correlation is not causation. As Nunes's paper (2016) also agreed that the duration of EV charging is longer than conventional parking, it is likely to lead to a deterioration of urban resources issues such as the lack of parking area and longer car park queuing time. It is especially crucial for a parking space with the highest densely populated like City Hall (in the Central District) with only 170 parking slots for private vehicles in total (Transport Department, 2021). If EV drivers feel difficult to find parking slot for recharge, it is likely to reduce the motivation of entering EV driving for potential EV consumers which leads to the obstacle of EV popularisation.

In furtherance, the 2021 car park utilisation in City Hall is predicted to increase based on the regression model (Figure 16). The prediction line presents a sequential fluctuation curve over time. The nadir of the regression line remains almost the same when the number of first registered EV is above 1 (after standardisation). Based on the pattern of the past data, at the very least, the beginning of 2021 City Hall data is expected to appear an upward trend. Along with the incentive policies under the EV popularisation roadmap and the increasing trend of EV first registration (Figure 6), the limited 170 parking slots will suffer incremental availability pressures to serve the EV demand. Again, it will consequently bring a negative impact to the EV introduction in Hong Kong.

Interestingly, the enhancement of car park utilisation rate does not imply on public car parks by region (Figure 8). It has been revealed that the park utilisation rates in Kowloon and New Territories have a multicollinearity problem. It will undermine the statistical significance of an independent variable, therefore it is ignored from the discussion. Whereas, the parking usage in the Hong Kong region still holds a negative correlation with the target. It could be due to the imbalance incentive focus between private and public charging facilities. According to the roadmap (Environment Bureau, 2021), HK$2 billion is going to spend on subsidising the installation of charging infrastructure for around 60,000 parking spaces in existing private buildings. In contrast, public parking spaces are benefited by HK$120 million in government-owned car parks solely. When there are limited parking slots with EV charging in public car parks, while the greater incentives of private EV infrastructure, drivers are likely to switch to recharge in private parking spaces such as those inside the commercial buildings. This could explain the negative correlation of parking usage in the Hong Kong region.

<u>10.4 The impacts of electricity consumption</u>

Four types of electricity consumption show a slightly positive correlation with the number of first registered EV (Figure 8). It is reasonable that the growth of the use of EV would lead to an increase in electricity consumption since EV relies on electricity. Consistent with the literature (Freund, Lützenberger and Albayrak, 2012; Galus *et al.*, 2013; Shepero and Munkhammar, 2018), consumption in domestic (home) and commercial (workplaces) fields are the most related features to EV.

Yet, the correlation of the electricity consumption on industrial and street lighting could be irrelevant due to the research choice of electric private cars. It is because EV for goods transportation such as electric trucks are not considered in the dependent variable. Consequently, using the electric private cars data for industrial/ street lighting correlation analysis is likely to reach an inaccurate conclusion. To avoid it, these two features will be excluded from the discussion.

Switching back to the focus of domestic and commercial, the coefficient values are approximately -0.17 and 1.03 respectively (Figure 10). Two main possible reasons could result in such negligible electricity consumption.

<u>10.4.1 Limited impacts brought by non-quick chargers</u>

First of all, non-quick charging does not pressurise heavily on the current electricity consumption in Hong Kong. Electricity consumption depends on the frequency of usage and the use voltage. In regard to the current EV network in Hong Kong, quick chargers proportionate at about 16% of the total EV chargers but medium chargers contribute around half of the total supply (Environmental Protection Department, 2021). When installing more EV medium chargers in government-owned car parks will be one of the focuses of the road map, the electricity usage is going to be affected mostly from medium chargers. With this voltage, the average electricity consumption of an EV can be as low as 0.20 kilowatt-hours per kilometre (Virta, 2021). Even the use of EV keeps increasing, the impact on the total electricity usage in Hong Kong is unlikely to be significant unless the charging network turns into massive quick chargers based (higher use voltage). In which, this finding counters the argument that electricity transmission is a concern of the use of EV mentioned by Situ and Mullan (2011). The current and following increased use of EV medium chargers might not multitudinously pressurise the electricity transmission in Hong Kong.

<u>10.4.2 Relatively low electricity consumption contributed by EV</u>

Moreover, the share of total electricity consumption by EV is also limited. Although the electricity dataset is restricted in showing the aggregated consumption but not by EV, referring to the situation in other countries could provide relevant insight on the same problem. According to International Energy Agency (IEA, 2020), the share of total electricity demand by EV in Europe was 6% in 2019. Compared to Hong Kong, the EV market share in Europe was around 14.7% meanwhile Hong Kong remained at around 2% market share (Kane, 2021; Legislative Council Secretariat, 2021). Given that Europe was in an even more dominant position in EV popularisation, the electricity consumption still contributes unremarkably to its aggregated figure. Thus, the use voltage of EV charging is unlikely to significantly influence electricity consumption in terms of domestic and commercial use. Such a small coefficient might only be able to show the correlation but not the causation in terms of the research topic.

11. CONCLUSION

This research aimed to identify the impacts of electric vehicles infrastructure on the current urban resources under the Hong Kong Roadmap on Popularisation of Electric Vehicles, in specific of car park crowdedness and electricity consumption. Based on data analysis with the combination of literature review, it can be concluded that the deterioration of parking usage is likely to appear following the introduction of EV. On the other hand, it does not imply the same situation towards electricity consumption under the specification of the current EV infrastructure. The data results further support this interpretation through the excessive correlation coefficient on government-owned car park utilisation rate and the low coefficient on electricity consumption.

The methodology has successfully provided insights under a limited amount of publicly available datasets on this topic. Most of the findings have matched with the research objectives and expectations made by the literature review. In terms of the research result, this paper has complemented the existing research gap in this area with several contributions of the interpretation. For example, it has updated the recent EV situation in Hong Kong and discussed the most significant results, including indicating the imbalance of EV charger distribution among districts and highlighting the busyness of government-owned car park in City Hall following the growth of the first registered EV. Besides, this research clearly reflects that the discussion of the impacts of electricity consumption by EV cannot be applied to the case in Hong Kong. Meanwhile, it also raises the question of the exact electricity consumption level by EV due to the lack of data. But as mentioned in section 8, we believe that the impact of electricity consumption by EV is able to reflect through an aggregated figure.

Based on these conclusions, there are two recommendations for EV popularisation in Hong Kong. Firstly, the focus of installing more charging stations in the surroundings is needed. As mentioned above, an imbalance EV charger distribution appears currently. By equally distributing EV charging stations, it will enable to widely expand the EV infrastructure in a city and further attract a larger amount of potential EV drivers. Secondly, the roadmap should concentrate more on building fast-charging stations instead of standard/medium chargers. The current strategy is to subsidies private parking spaces in installing medium chargers (Environment Bureau, 2021, p.20). As discussed, long charging duration (low charger voltage) would impact the car park crowdedness, and the level of convenience could lower the use of EV. If the purpose is to massively popularise EV, the Hong Kong government should support and install fast-charging stations directly and widely. It is because a fast-charging station can provide a shorter recharging duration and to accelerate the parking slot turnover rate (reduce car park crowdedness and serve more EV in a car park). These two suggestions are the possible direction for people who may want to investigate this topic further in the future.

Lastly, to better understand the implications of these results and interpretations, future studies could address the influences of massively adopting a fast-charging station as suggested above. Electricity transmission may be a concern in this case since the charger voltage increase, which has not been discovering in this dissertation. Additionally, further research is needed to determine the impacts of both urban resources for each district in depth. This direction could reflect a dissimilar conclusion since the population and level of income (affordability of buying an EV) of each district are different. Likewise, it would depend on the accessibility of the relevant datasets. Besides, this research question has high complexity as it cannot be concluded by only two factors. In line with the findings and literature, related areas such as the convenience of EV charging stations and the temperature in car parks caused by charging (since most chargers will/ are built inside a car park) have not been investigating in this paper. It can also be a future research direction. In summary, this dissertation only investigated two possible aspects of the impacts on the introduction of EV. Installing more charging stations could build a user-friendly environment for encouraging the use of EV in Hong Kong, but the popularisation of EV should consider several stakeholders simultaneously.

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