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Lessons learned from EV charging infrastructure in mega cities: A data-driven approach

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ABSTRACT

E-mobility has witnessed a major evolution in the last couple of years due to climate action concerns. Cities that have employed e-mobility across the globe can be classified into two groups: e-mobility forerunners and cities at the early market stages of e-mobility. Electric Vehicle Charging Infrastructure (EVCI) is one of the main pillars of e-mobility rollout. Thus, it is important to investigate the lessons learned from EVCI installation across those forerunner cities around the world. This research addresses a data-driven multi-dimensional serviceability analysis of EVCI in 25 cities across the globe, to unveil many of those complex patterns associated with EVCI planning by discussing: EVCI service coverage, radius, and standard evaluation metrics. City comparisons, market patterns, and worldwide trends have been observed and geo-spatially analyzed including: 1) EVCI coverage vs EVs sales, 2) density distribution of charging pools/1km^2 covered cell, 3) the analogy between demand-driven networks and density distribution of EVCI locations, 4) the structure of EVCI covered areas in relation to cities' urban fabric, 5) charging pools/million population in relation to the type of parking citizens have access to and drivers' charging preferences, 6) the effect of road network topology on EVCI service radius, 7) the effect of prevalent degree of electrification and traffic conditions on EVCI service coverage and radius, and 8) the effect of ambient temperature on EVCI service radius. Other factors related to e-mobility public policies (such as: EVCI incentives) have resulted in – along with cities' characteristics – different levels of success across the studied cities. The provided analysis shall help in: 1) providing e-mobility early adopters' cities with a high-level guidance on the best practices for EVCI planning, 2) spreading the praiseworthy EVCI installation practices among e-mobility forerunners to further optimize EVCI deployment.

1. Introduction

The transport sector accounts for more than one-quarter of energy-associated greenhouse gas emissions, becoming the quickest evolving source of emissions, and without a robust act, it could be doubled by 2050 (Sustainable Mobility for All, 2021). Global authorities initiated vigorous steps to reduce global warming and attain the targets of the Paris Agreement, an international treaty that aims to reduce climate action to less than 2 °C or ideally to 1.5 °C in comparison with pre-industrial levels. International conferences, like Conference of the Parties[1] (COP), are also held annually to follow up on the actions and policies adopted by the registered countries concerning climate action.

E-mobility could be one of the attributes towards a clean transition of the transport sector. Concerns about climate and greenhouse gas emissions is one of the factors that have caused the revival of EVs in the mid-1900s (Chan, 2012). However, depending solely on e-mobility won't attain the climate targets. There are limitations related to: national energy systems and attributed environmental injustice, impact on the power grid, as well as material availability for batteries' manufacture. For example, according to (International Energy Agency, 2021), the main source for electricity production in China is coal. The environmental injustice that has occurred in some municipalities like Shanghai, Beijing, and Shenzhen, due to electrification, has been highlighted by (Bai et al., 2021). They have stated that EVs depend mainly on electricity for charging, which transfers the problem to the locations of power plants if it is still running on fossil fuels for electricity generation. From another perspective, (Milovanoff et al., 2020) have discussed limitations related to the availability of materials – lithium, cobalt, and manganese – needed to produce lithium-ion batteries to sustain the required growth of EVs in the U.S. They have concluded that it is not practical to depend

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[1] Usually attended by countries that have signed the United Nations Framework Convention on Climate Change (UNFCCC).

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only on EVs to cover the gap of LDV fleet's CO_2 emissions in the U.S. Multimodality and the transition to more efficient and cheap modes along with existing fleets electrification while maintaining greening of the grid, should be the combined focus of policies to attain climate targets. This shall make the best use of e-mobility while enlarging its role in sustainable mobility development (Sustainable Mobility for All, 2021).

The wide spread of e-mobility is governed by the availability of robust charging infrastructure. People have a due concern about EVs range. Despite the complexity of the problem, involving multi-parties (technological, environmental, economic, transport, governmental, etc.), some cities have successfully managed to promote e-mobility and reduce the footprint of CO_2 emissions. Thus, it is crucial to follow the successful footsteps of those leading cities and learn about their characteristics, maturity level concerning e-mobility market, EVCI size and locations, in addition to the policies adopted for promoting EVCI. This shall provide a guidance for cities at the early market stages of e-mobility to adopt the best practices of EVCI installation. Moreover, it will spread these practices among e-mobility forerunners so as to further refine future EVCI installation.

This research adopts a data-driven approach to highlight lessons learned from EVCI planning in chosen Mega EV cities. Previous research efforts have adopted data-driven approaches to optimize EVCI planning as in (Sun et al., 2023), (Hung & Michailidis, 2022), (Y. Yang et al., 2020), (Zhou et al., 2020), (Q. Liu et al., 2019), (J. Yang et al., 2017), except for (Antoun et al., 2021), where they have adopted a data-driven approach to enhance the quality of service (QoS) of public charging stations using real data in Quebec, Canada. This research is the first – to the best of our knowledge – that uses a data-driven approach to assess the development of EVCI among e-mobility forerunners around the globe in relation to cities' characteristics and factors affecting EV range. This in-turn shall underscore the key lessons learned, cities should consider, to enhance EVCI expansion (for e-mobility forerunners) or to have a robust start of e-mobility rollout (for cities at their early market stages of e-mobility).

This research aims to: a) summarize previous research approaches concerning optimal siting and sizing of EVCI, b) investigate different elements affecting EV energy consumption and range, and thus EVCI serviceability, c) model the relationship between those elements and EVCI serviceability in selected Mega EV cities to unravel any existing patterns, d) outline the key lessons learned from EVCI planning and implementation in those Mega EV cities, and e) investigate how do these lessons relate to cities' urban fabric, and how transferable are these lessons. This analysis shall be a first step towards establishing a framework for EVCI planning based on lessons learned from e-mobility forerunners.

The remaining of this article is structured as follows: Section 2 presents previous research efforts in EVCI planning with a detailed review of the problem dimensionality considered in this research. Section 3 presents a general overview of the research methodology with a more detailed discussion on cities of scope and their characteristics, as well as EVCI database development, spatial modeling, and quality review. Section 4 presents the multi-dimensional serviceability analysis of EVCI and lessons learned from Mega EV cities. Section 5 provides a summary of the key findings, limitations, and recommendations for future works.

2. EVCI planning background and the intertwined cycle between EVCI, EV type, energy consumption, and cities' urban fabric

The problem of EVCI placement has been addressed in literature from four different perspectives: a) objective functions (21 %), b) solution techniques (57 %), c) geographic conditions (15 %), and d) demand side management (7 %) (Bilal & Rizwan, 2020). Costs (like installation, accessibility, operation, and travel time) in addition to electric power-related factors, are examples of the objective functions that have been addressed in literature for the optimal placement of EVCI. The constraints of these functions were divided between transportation and power sectors. Examples of the transportation sector's constraints are: budget, number of chargers, distance, traffic flow, and driving range. For power sector's constraints, it includes: power flow, charging demand, voltage limit, and thermal limit. Solution algorithms used for solving EVCI placement included particle swarm optimization (PSO) used by 20 % of researchers, genetic algorithm (GA) by 17 %, linear integer programming by 17 %, ant colony optimization by 11 %, and the remaining 35 % used miscellaneous techniques.[2]

For geographic conditions perspective, it depends on maximizing the served flow of EVs while locating EVCI. Finally, demand-responsive programs aim to make consumers leverage their energy usage efficiency in peak hours vs off-peaks. It is divided into: a) time-based programs which are based on different prices of electricity at different times based on the price of energy supplied (like time of use, real-time pricing, and critical peak pricing), and b) Incentive-based programs which are developed to make users harness their energy usage (like direct load control, interruptible services, capacity market programs, demand bidding, and ancillary services market) (Bilal & Rizwan, 2020).

The following subsections shall introduce: essential definitions of EVCI, EV types, factors affecting EV energy consumption, and different elements of cities' urban fabric. These perspectives will be influential in this research while analyzing the problem of EVCI location in Mega EV cities.

2.1. EVCI hierarchy and accessibility

There are various global nominations for EVCI hierarchy. The Sustainable Transport Forum (STF) originated by the European Commission classifies EVCI from large to small into: charging pool, charging station, charging point, and charging connector/outlet (Visser, 2019), as shown in Fig. 1a. An illustration of these levels is provided in Fig. 1b.

A charging pool is defined as a location with several charging stations with one charge point operator (CPO). For example, car parks, fueling stations, supermarkets, etc. A charging station is defined as an equipment with one user interface, attached to the wall or free-standing. It is connected to an electrical source that can charge multiple vehicles based on the number of available charging points. A charging point or Electric Vehicle Supply Equipment (EVSE) charges one vehicle at a time. Finally, a charging outlet or connector is the physical linkage between a charging point and an EV, and through which electricity feeds the vehicle up. It can be a socket, cable, pantograph, or an induction plate as depicted in Fig. 2.

From another perspective, EVCI can be categorized considering its accessibility into: public, semi-public, and private (Singh et al., 2021). Table 1 shows the difference between the three types with respect to utilization, possible locations for installation, ownership, and the entity in charge of the operation. These categories are not rigid; some charging facilities can exhibit hybrid characteristics. For example, EVCI owned by fleet operators for restricted use is private. However, it can be a public one if opened for all EV users as a paid service, when fleets are in operation (Singh et al., 2021).

2.2. Degree of electrification and factors affecting EV energy consumption

According to (Mahmoudi et al., 2014), there are three types of EVs: Battery Electric vehicles (BEVs) or All-Electric Vehicles (AEV), Hybrid/Plug-in Hybrid Electric Vehicles (HEV/PHEV), and Extended Range

[2] Examples are: greedy algorithm, bi-level programming, Nested Logit Model, Bayesian Game, Bender's decomposition algorithm, active-set technique, fuzzy Delphi method, Grey relation analysis-VIKOR, CPLEX Software, extended flow refueling location model and charging pad, as well as Voronoi diagram and queuing theory (Bilal & Rizwan, 2020).

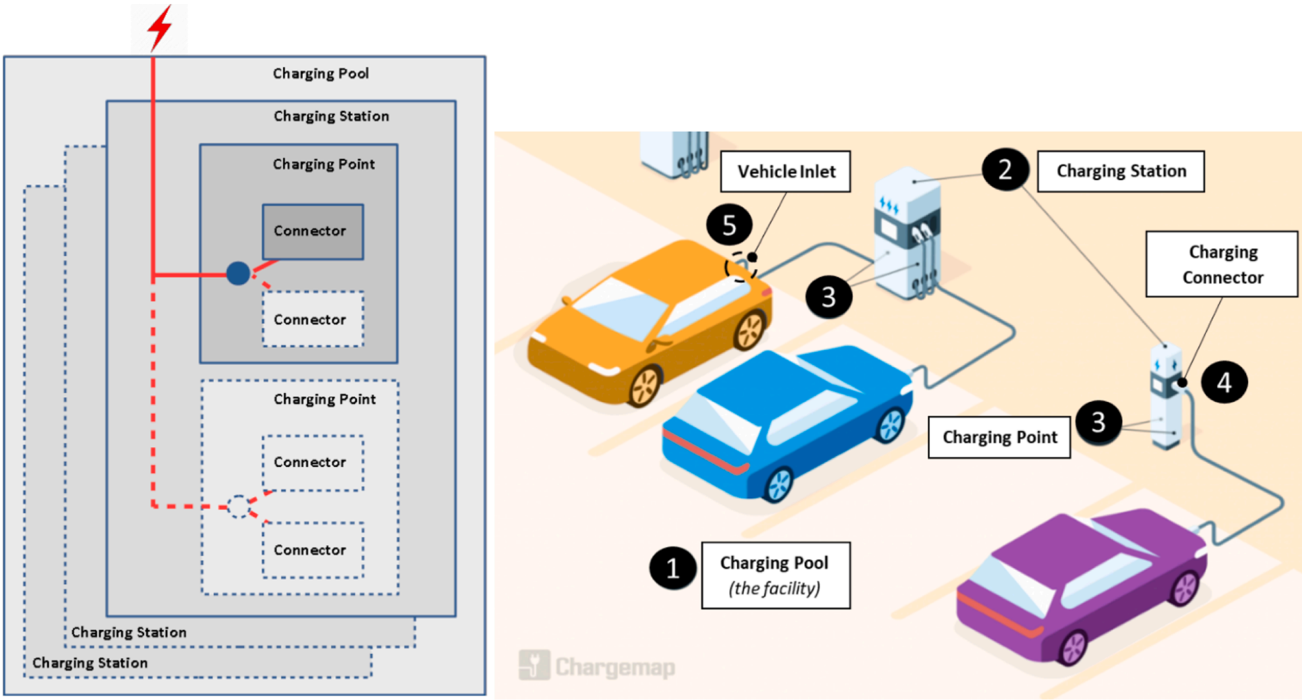


Fig. 1. EVCI Hierarchy. a) STF Classification (Visser, 2019), b) Example on STF Classification; A charging pool with three charging stations and six charging points *adopted from* (Anatomy of a charging pool for electric vehicles, 2020).

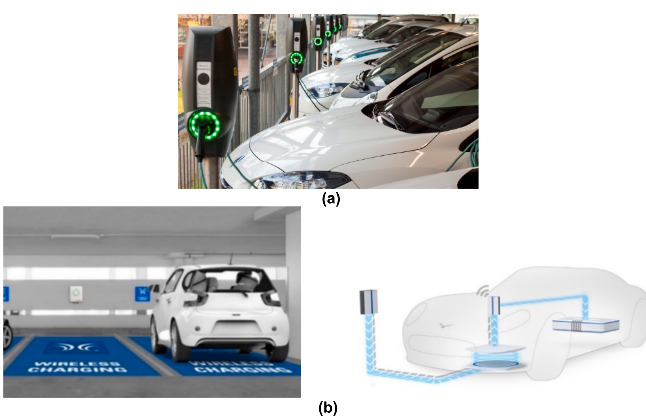


Fig. 2. An illustration of EV charging outlets/connectors. a) EV charging cables (gtm, 2018), b) EV induction plates (a.k.a., wireless charging) (GREEN CAR REPORTS, 2020) (CircuitDigest, 2019).

Electric Vehicle (EREV). In addition to those three main types comes the Fuel Cell Electric Vehicle (FCEV), and Solar Electric Vehicle (SEV).

BEVs contain high-capacity batteries and electric motors for vehicle propulsion. HEVs and PHEVs contain a combination of an electric motor and an internal combustion engine for vehicle propulsion. The main difference between HEV and PHEV is that the latter has a new battery charging system that can be filled externally and the internal combustion engine acts as a reserve when batteries are consumed. However, both HEVs and PHEVs can be charged using regenerative braking.[3] For EREVs, the electric motor operated by high-capacity batteries is the primary source of the vehicle's movement. Those batteries are kept charged by a small generator running on an internal combustion engine, thus offering an extended range than BEVs. FCEVs use a fuel system running on hydrogen fuel reserved and oxygen from the air to power the electric motor. Finally, SEVs are mainly driven by direct sunlight which is introduced to the vehicle as electric energy by solar arrays (usually are photovoltaic cells) installed on top of the vehicle. It can also be supplied with a battery pack to guarantee sufficient range during shaded days or nighttime (Mahmoudi et al., 2014).

This research focuses on BEVs and PHEVs. According to the (Alternative Fuels Data Center, 2021) in the U.S. Department of Energy, BEVs must be charged using a charging station or a wall outlet, whereas PHEVs' batteries can be charged using a charging station, a wall outlet, or by the internal combustion engine (ICE). Although PHEVs can be fueled using conventional fuel stations, thus it wouldn't be crucial to always use EVCI, the relationship between the prevalent type of an EV in a city and the coverage extent of EVCI wasn't addressed in previous research work. If considered, this factor could be beneficial for cities at the early market stages of e-mobility. These cities might not have to invest largely in EVCI coverage and shall compensate this by partially depending on existing conventional fuel stations.

Regardless of the EV type, there is a consensus on some factors affecting EV energy consumption and thus EV range. Traffic conditions and ambient temperature are widely addressed in literature as factors affecting EV energy consumption. Traffic conditions is classified as a micro factor affecting EV energy consumption (Hu et al., 2017). Previous research efforts that have considered this factor were conducted on a road-level analysis. The most explicit model found in literature was deduced by (Fiori et al., 2019) in Antwerp, Belgium, where they proved that EVs consume less energy in congested conditions than in free-flow conditions. They concluded that there is a quadratic general trend between average speed and energy consumption, with approximately a constant energy consumption till 50 km/h, then an increase occurs relative to higher speeds.

For ambient temperature factor, the literature investigation has been structured into 3 verticals: relationship between ambient temperature

[3] Regenerative braking is a technology that makes the best use of the kinetic energy generated while braking, by converting most of it to electric energy to be stored inside the battery.

Table 1
Difference between public, semi-public, and private charging *adopted from* (Singh et al., 2021).

Charging Type	Usage	Location Examples	Ownership	Operation
Public	Open for all EV users	On-street parking and Public Parking Lots	Municipal Authorities, Public Sector Undertakings (PSUs), Charge Point Operators (CPOs), and Host Properties	CPO-administrated
Semi-Public	Shared charging for a limited group of EV users	Apartment Campuses, Shopping Malls, Universities, Hospitals, Office Campuses, and Government Buildings	Host properties, Original Equipment Manufacturers (OEMs), and Charge Point Operators (CPOs)	CPO-administrated
Private	Devoted for personal EV or EV fleet owned by one organization	Detached homes, Dedicated Parking Spots in Houses/Workplaces; for fleets – any place with land availability	Personal EV owners, EV fleet owners/ operators	Self-operated or CPO-administrated (for EV fleet charging)

and energy consumption, relationship between ambient temperature and EV range, and finally the relationship between energy consumption and EV range (Fig. 3). When investigating the first vertical; (Al-Wreikat et al., 2021), (P. Li et al., 2021), (Yi et al., 2018), (Taggart, 2017), (Fiori et al., 2016), and (Yuksel & Michalek, 2015) works have complied with what (K. Liu et al., 2018) have concluded, where the relationship between ambient temperature and energy consumption per kilometre in Aichi Prefecture, Japan, followed an asymmetrical U-shaped distribution. They concluded that extreme hot and cold ambient temperatures had the highest energy consumption, whereas the highest energy efficiency was in the range of 21.8–25.2 °C. For the second and third verticals, (Iora & Tribioli, 2019), (Fiori et al., 2016), and (Yuksel & Michalek, 2015) have shown that as the energy consumption increases at different ambient temperatures, EV range decreases.

Though the significant impact of traffic conditions and ambient temperature on EV energy consumption and thus on EV range, their effect on EVCI planning hasn't been explicitly concluded – to the best of our knowledge – in previous research works.

2.3. *Cities' urban fabric: Settlement patterns, road network topology, land uses, and generation of demand driven networks*

Settlements are defined as places where people live. There are three types of settlement patterns, classified as follows: nucleated, linear, and dispersed (Haughton, 2021). This classification depends on the shape of populated areas, which is based on the surrounding physical topographic restrictions. The effect of settlement patterns hasn't been investigated in literature in relation to the structure of EVCI covered zones in a city. If considered, this could imply – from high-level planning – the prediction of EVCI covered zones' structure to be developed in a city.

For the road network connecting EVCI, earlier studies have often classified street networks in a city into grid, radial, circular, or their combination (Y. Li & Tsukaguchi, 2005). The more the network is centralized, the more connectivity it provides (Derrible, 2010). Therefore, considering the extreme cases: radial networks provide the highest connectivity while grid networks have the lowest connectivity. The effect of road network topology on the connectivity of EVCI network wasn't addressed in previous research works. The inclusion of this factor is of due importance for planning and evaluation purposes within the same city with a hybrid road network topology, and between cities for comparing performance efficiency.

Where an EVCI is eventually planned to serve EV demand whose size depends on the type of surrounding land uses, it wasn't proven that existing EVCI networks are demand-driven. This is crucial for evaluating EVCI distribution and bridging any unforeseen gaps. The concept of demand-driven networks has been discussed by (Derrible, 2010), where he stated that the U.S. air traffic system is demand-driven with a power-law distribution. Hubs are created at the tail of the curve with an improper number of connections compared to compact airports at the other side of the curve (Fig. 4a). (Derrible, 2010) has further illustrated that this distribution entails a scale-free network structure, where the probability f that a vertex v has b connections pursues a power-law distribution as depicted in Eq. (1). The factor $\in$ is called the scaling factor, whose value describes much about the characteristics of a network. Fig. 4b shows two main trends; aristocratic and egalitarian patterns. When $\in$ is very small, this entails a slower decay or a fat-tail of the curve where there is a larger presence of points with many

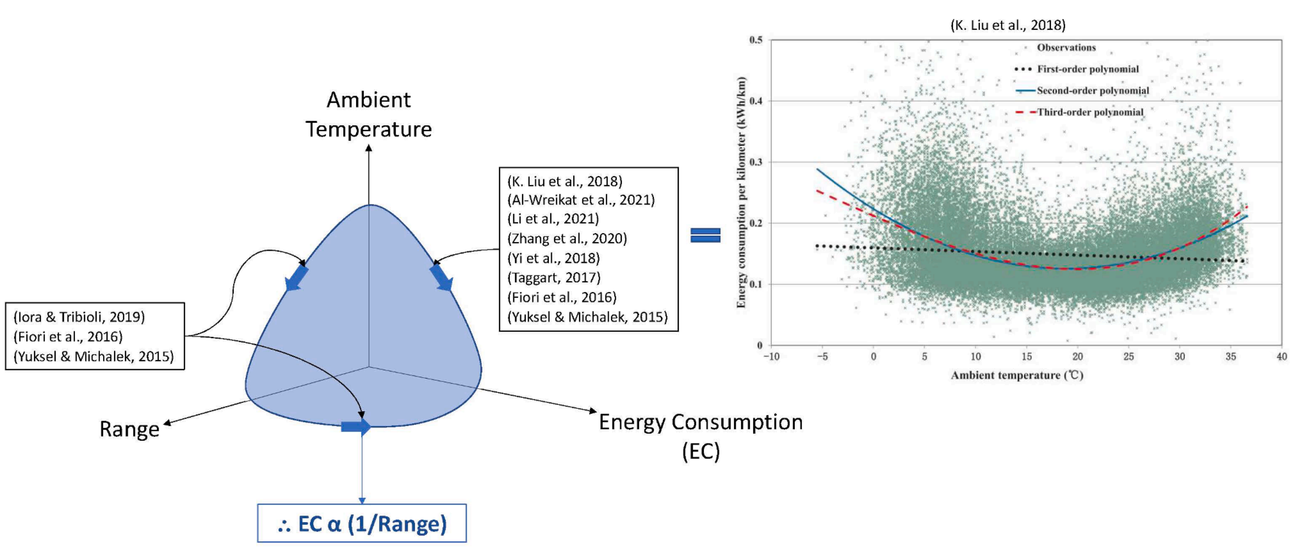


Fig. 3. **Relationship between Ambient Temperature, Energy Consumption, and EV Range.**

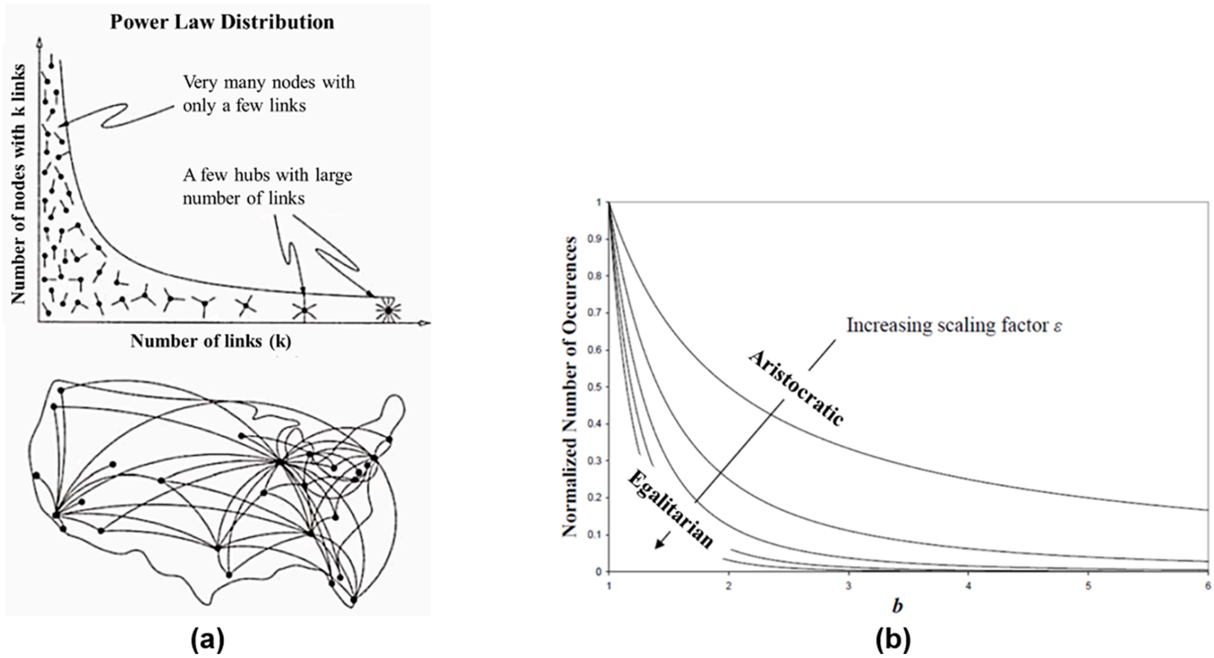


Fig. 4. The Concept of Demand Driven Networks and Power Law Trends (Derrible, 2010). a) Structure of the U.S. Air Traffic System (demand-following), b) Relationship between the scaling factor ε and normalized frequency distribution.

connections ***(aristocratic pattern)***, whereas, when ∊ is very large, this indicates that few points are with many connections "thin-tail" ***(egalitarian pattern)*** (Derrible, 2010).

$$f(b) \propto b^{-\epsilon} \tag{1}$$

As discussed in the previous sections, notable research efforts have embarked in planning of EVCI. However, most studies were done in silos, with no serious attempt to unveil the intertwined factors affecting EVCI planning across cities and within cities considering: energy consumption, degree of electrification, cities' urban fabric, and various accessibility types of chargers. Understanding the intertwined effect of these factors on EVCI serviceability shall be a first step towards establishing a framework for EVCI planning that can be projected on any city based on its characteristics. The next section articulates the proposed approach to a data-driven multi-dimensional serviceability analysis of EVCI.

3. Methodology

The methodology presented herein provides a data-driven approach to outline lessons learned from EVCI planning in selected Mega EV cities through a multi-dimensional serviceability analysis targeting: EVCI service coverage, service radius, and standard evaluation metrics. Fig. 5 provides a comprehensive illustration of the data-driven multi-dimensional serviceability analysis architecture conducted in this research. The architecture starts with determining and justifying cities of scope. These cities have been selected due to: their representative geographical distribution, their different market maturity levels, as well as their valuable policies and actions concerning EVCI, as will be discussed in next sections.

Afterwards, cities' characteristics shall be defined. These characteristics are divided into two categories based on whether the data have been directly collected for cities of scope or have further undergone a data analysis process. The main objective is to label each city with its distinct characteristics to investigate market/global patterns of EVCI distribution in relation to these characteristics. This is anticipated to provide a synopsis of the ongoing framework for EVCI installation and identify key lessons learned from the studied cities and more importantly the transferability of these lessons to other cities. Next, EVCI database development will be introduced, with a thorough illustration of the procedures followed to make sure data is reliable.

To that end, EVCI multi-dimensional serviceability analysis in the chosen Mega EV cities shall be introduced, focusing on three verticals: service coverage, service radius, and standard evaluation metrics. EVCI service coverage is concerned with the percentage of a city area covered with charging infrastructure, the density of charging locations, and the number of charging locations/million population. EVCI service radius is concerned with the spacings between charging locations, where two measures have been identified: 1) measure of centrality; as if one randomly points out a location on a city map, by how many kilometers radius it is expected to find a charging location, and 2) measure of proximity; as, if one is at an existing charging location, it is expected to find the next charging location within how many kilometers. City-city comparisons, market patterns, and worldwide trends have been observed and geospatially analyzed. Sensitivity analysis has been also done to explore the effect of cities' characteristics including: traffic conditions, ambient temperature, and prevalent degree of electrification on the service coverage and radius of EVCI.

The last vertical is the standard evaluation metrics used in literature to evaluate EVCI. Key inputs from cities' characteristics and policies adopted for promoting EVCI have helped in unveiling cities' different levels of EVCI distribution. An example of three cities (Oslo, Amsterdam, and Shenzhen) will be provided as an illustration of the observed patterns.

At this step, lessons learned from EVCI planning in Mega EV cities are marked. The transferability of these lessons is of due importance for cities at the early market stages of e-mobility; to guide them through the best practices of e-mobility rollout, as well as for other e-mobility forerunners; to further enhance future EVCI installation.

The following subsections shall include: 1) defining and justifying cities of scope, 2) listing the different characteristics of these cities included in this research, and 3) detailing the effort exerted in the collection, filtration, and quality review of EVCI locations in the chosen Mega EV cities, thus finally make those cities ready for the geospatial multi-dimensional serviceability analysis.

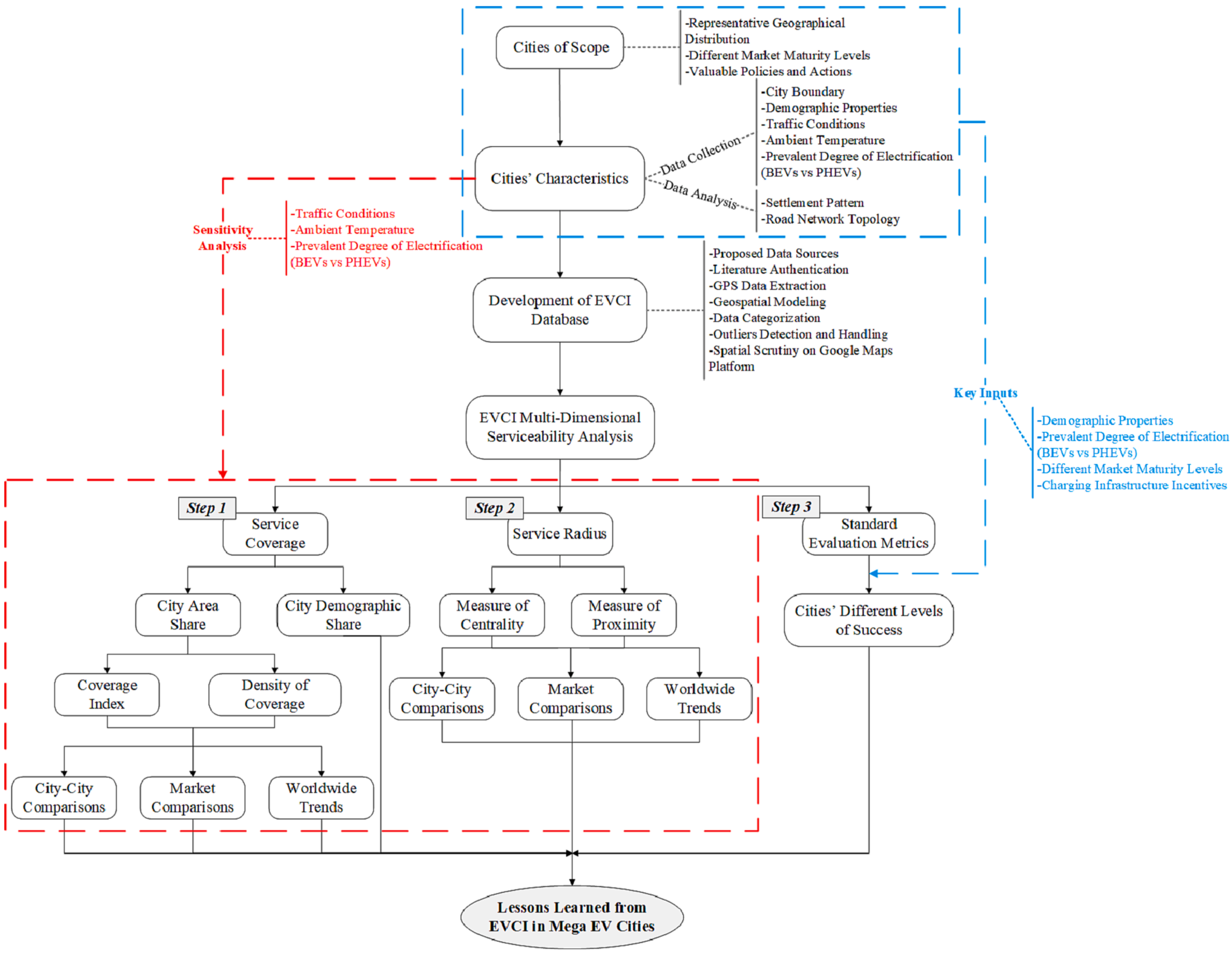


Fig. 5. **Overview of the Data-Driven Multi-dimensional Serviceability Analysis Architecture of EVCI in Mega EV Cities.**

3.1. Cities of scope

The selected cities of scope are inspired from (Hall et al., 2020), where they have listed the top global 25 electric passenger vehicle capitals based on the cumulative sales from 2010 to 2019, specifically targeting two types of electric passenger vehicles: BEVs and PHEVs (Fig. 6). The reasons for selecting these cities are: 1) their representative geographical distribution, 2) their different market maturity levels considering EVs sales and market categories of consumer,[4] thus one can track different levels of success, 3) the transferability of the policies and actions originally generated in these cities to other countries, which indicate that these lessons are valuable to highlight.

Cities with Representative Geographical Distribution: The distribution of these cities is as follows: 60 % in Asia, 24 % in Europe, and 16 % in North America, thus the study scope will not be biased to a certain region.

Cities with Different Market Maturity Levels: As shown in Fig. 6 China has shown a tremendous control over the scene preceding just before Europe, the U.S., and Japan. In Fig. 6, (Hall et al., 2020) have also plotted the share of EVs considering the 2019 new passenger vehicles sales. Bergen and Oslo have taken the lead with 67 % and 64 % respectively, entering the late majority phase as per the market categories of consumer (Fig. 7). Fig. 6 and Fig. 7 show that most EV capitals were in the early adopters' phase in 2019 except for Shenzhen, Liuzhou, San Jose, Stockholm, and Amsterdam, being in the early stages of the early majority phase.

Cities with Valuable Policies and Actions: The share of these 25 capitals in the global EV market has shown a gradual annual decline from 2016 till 2019 as follows 45 %, 44 %, 42 %, and 40 % respectively. This means that the market is expanding beyond them indicating that the policies and actions originally evolved by these capitals are making their way out in other cities (Hall et al., 2020). Therefore, the robust and mainstream e-mobility strategies of these capitals are still valuable lessons to highlight and that's why this research will focus its analysis – taking 2019 as the reference year of study – on them being in that mature stage.

3.2. Cities' characteristics

As mentioned earlier, cities' characteristics were divided into two categories based on whether these data have been directly collected or analyzed. Cities' characteristics that have undergone data collection process include: city boundary, demographic properties, traffic conditions, ambient temperature, and prevalent degree of electrification. City

[4] Consists of 4 phases: "Innovators" comprising the first 2.5% of the market, "Early Adopters" resembling the following 13.5%, "Early Majority" with the next 34%, and finally the remaining 50% are for "Late Majority"(Hall et al., 2020).

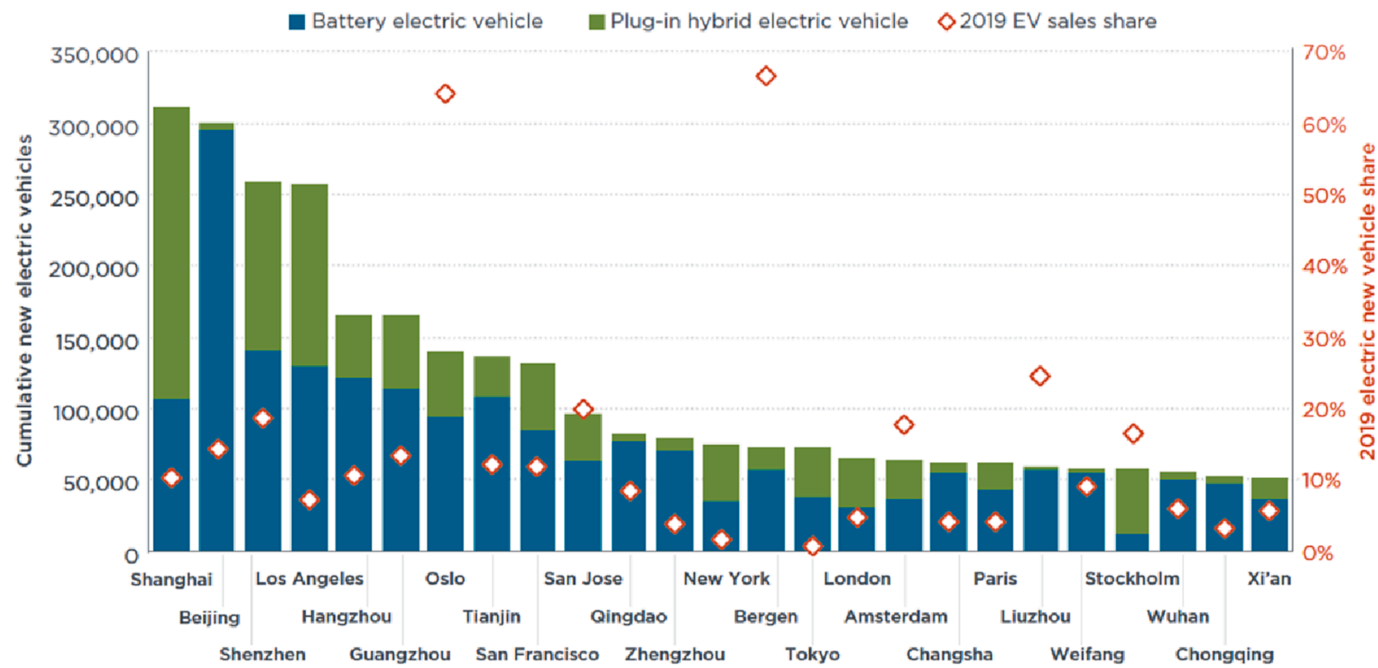


Fig. 6. Cumulative new e-passenger vehicles/share of new passenger vehicles – 2019 in Mega EV cities (Hall et al., 2020).

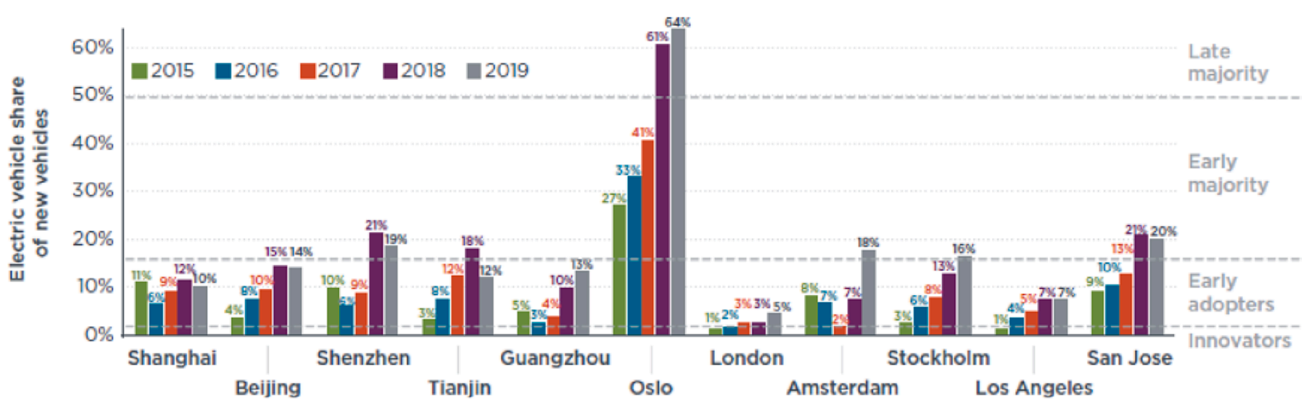


Fig. 7. Market Categories of Consumer for Selected EV Capitals (2015–19) (Hall et al., 2020).

boundary is used for defining the physical bounds of a city. Demographic properties indicate the size of a city. Traffic conditions and ambient temperature data represent the operating conditions of EVs in each city which affect their energy consumption and thus their range.

All cities' boundaries are referenced to Berkeley Library Geodata, except for the U.S. cities, which are referenced to the United States Census Bureau. For the demographic properties, *worldatlas.com* and *worldpopulationreview.com* are used as a reference for 2020 population record. Using TomTom city size classification by population,[5] most of the studied cities were classified as mega cities (13 cities out of 25) while the remaining cities were large (11 cities out of 25), except for Bergen which was classified as a small city. For traffic conditions data, TomTom 2020 congestion level is identified for each city, which represents the excess amount of time that would be added to a trip time in uncongested conditions to represent rush hour conditions. Ambient temperature data is referenced to *weatherspark.com* platform, where it is categorized by season; hot/warm vs cold/cool. Average daily high temperature threshold is identified for each season as well as the extreme temperatures (hottest and coldest day) of the year.

For the prevalent degree of electrification, the focus of this research is on BEVs and PHEVs as depicted in Fig. 6. Considering that PHEVs can be fueled using conventional fuel stations, thus it wouldn't be crucial to always use EVCI (unlike BEVs), this inspired this research to answer the following questions: Did cities with dominant PHEVs didn't worry much about range anxiety as they already have existing fuel stations? Was this more economic in their early market stages to adopt PHEVs and not consider the high investment costs of charging infrastructure needed for BEVs? Are BEV cities, the forerunners concerning charging infrastructure coverage? Did these cities have much more connectivity and proximity of EVCI than PHEV ones?

From another perspective, cities' characteristics that have undergone data analysis include: cities' settlement patterns and road network topology as will be further discussed in Section 4.

[5] TomTom City Size Classification (by population): mega (>8 million), large (>800 thousand), and small (<800 thousand). To avoid confusion between TomTom city size classification by population "mega" and the chosen cities of study "Mega" EV cities, the following definitions should be considered: **mega city** is a city with population > 8 million. It is a demographic classification developed by *tomtom.com*. whereas **Mega EV city = EV Capital** refers to an e-mobility forerunner city = cities that are central in the e-mobility field.

3.3. EVCI database development

There are widely available published data sources for EVCI, thus, to verify a one for use, the effort in this research was structured as follows: 1) validate the data source usage in previous research work, 2) extract GPS data which sometimes needed a hybrid approach between used data sources and Google Maps platform, 3) spatial modeling of EV charging locations using QGIS, 4) harmonizing the hierarchy of charging infrastructure across used data sources, 5) outliers detection and handling, and 6) spatial scrutiny and review on Google Maps platform. To that end, cities of scope shall be ready for geospatial analysis. Fig. 8 shows the steps followed to develop cities' EVCI database. It is worth noting that EVCI data review was covered between 2021 and 2022.

3.3.1. Proposed data sources

Extensive research and outreach efforts have been exerted to

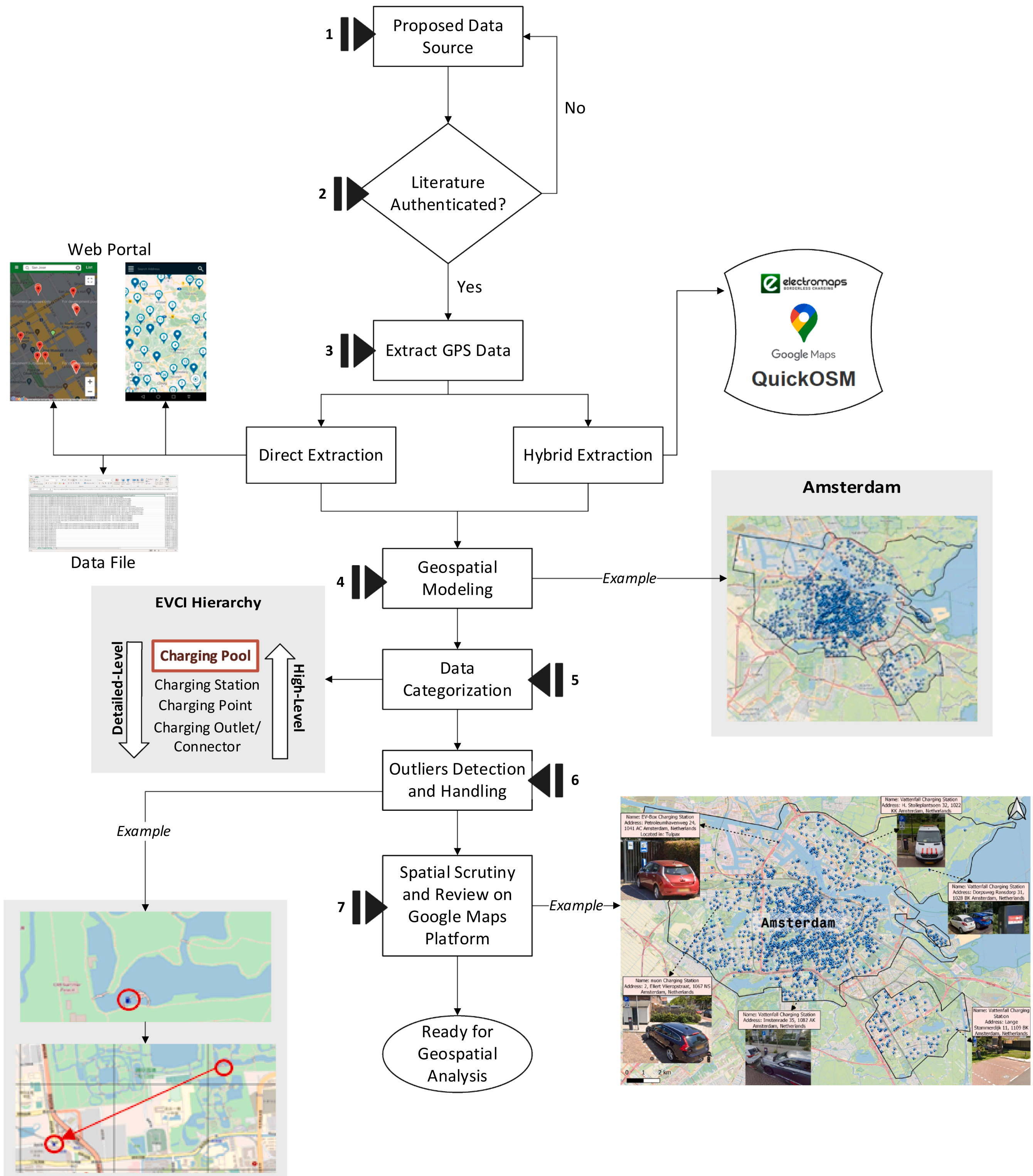


Fig. 8. EVCI Database Development and Quality Control Architecture.

establish solid EVCI database. The data sources' inspiration was based on EVCI data sources used by (Hall & Lutsey, 2020a), and are detailed for cities of scope in Table 2. Some of the cities' data sources are developed by the government like in the U.S (U.S. Department of Energy, n.d.). Others are open-source computer tool, that is made by government incorporations with EV associations and allows data extraction using an Application Programming Interface (API) (Nobil, n.d.), as in Norway (Kvisle, 2012). While others are an open-source directory for EV charging locations (LEMNET, n.d.) or a navigation map interface (Electromaps, n.d). Most of these data sources have developed a mobile application to provide users with real-time information about available charging locations. These applications allow for reporting a charging location along with its key parameters like name, address, type, charging power, number of connectors, payment type, company website, and so forth.

3.3.2. Prevalence of EVCI data sources in literature

To better judge the feasibility of using the above-mentioned data sources in this research, a comparative literature survey was conducted to understand the extent of adopting these sources (LEMNET, n.d; Nobil, n.d; Electromaps, n.d) in the relevant literature. Table 3 summarizes – to the best of our knowledge – the relevant literature that has used the same data sources. Some have used these data sources combined with other sources, then overlapping between data was removed (Nicholas & Wappelhorst, 2020). Some have addressed the credibility of these sources by stating that it contains a continuous update of EV charging stations' data in Europe (Betz et al., 2017). Other works have clearly stated the level of EVCI data given by a specific source whether it is a charging site or a charging point (Gnann et al., 2018). And finally, some have used data from these sources without mentioning any concerns related to data accuracy (Basmadjian et al., 2019), (Gnann et al., 2015), (Funke et al., 2015), (Gnann et al., 2018) (Harbo et al., 2018) (Lorentzen et al., 2017) (Bąk & Makolska-Tenold, 2017) (Mersky et al., 2016), (Haugneland & Hauge, 2015), (Kvisle & Myklebust, 2013), (Malinen et al., 2013), (Maza-Ortega et al., 2021), (Gómez-Mesino et al., 2020), (Jordán et al., 2018a), and (Jordán et al., 2018b); except for (Springel, 2017) where opening dates of charging stations were recovered based on contact with government sources as data was left-censored.

Table 2
EVCI Data Sources.

Country	City	Data Source
C	Shanghai	Electromaps
C	Beijing	Electromaps
C	Shenzhen	Electromaps
US	Los Angeles	U.S. Department of Energy
C	Hangzhou	Electromaps
C	Guangzhou	Electromaps
NR	Oslo	Nobil
C	Tianjin	Electromaps
US	San Francisco	U.S. Department of Energy
US	San Jose	U.S. Department of Energy
C	Qingdao	Electromaps
C	Zhengzhou	Electromaps
US	New York	U.S. Department of Energy
NR	Bergen	Nobil
J	Tokyo	QuickOSM Plugin in QGIS
UK	London	QuickOSM Plugin in QGIS
NTH	Amsterdam	LEMNET
C	Changsha	Electromaps
F	Paris	LEMNET
C	Liuzhou	Electromaps
C	Weifang	QuickOSM Plugin in QGIS
S	Stockholm	Nobil
C	Wuhan	Electromaps
C	Chongqing	Electromaps
C	Xi'an	Electromaps

C = China, F = France, J = Japan, NR = Norway, NTH = Netherlands, S = Sweden, UK = United Kingdom, US = United States.

Table 3
Prevalence of EVCI Data Sources in Literature other than (Hall & Lutsey, 2020a).

Data Source	Used by	Literature Type	Research Focus
LEMNET	(Nicholas & Wappelhorst, 2020)	White Paper	-Location of charging stations
	(Basmadjian et al., 2019)	Conference Article	-Location and number of charging stations
	(Betz et al., 2017)	Conference Article	-Location of charging stations
	(Gnann et al., 2015)	Conference Article	-Location and number of charging stations
	(Funke et al., 2015)	Book Section	-Number of locations, stations, and sockets for public charging -% of charging stations operated by public utilities and local energy providers -% of non-public charging infrastructure that can be used free of charge -Number of charging points per charging station
Nobil	(Gnann et al., 2018)	Journal Article	-Real-world charging data; start time of charging events, connection time, and station specifications such as power rating and connector plug type -Number of charging sites
	(Harbo et al., 2018)	Conference Paper	-List of charging stations, their location, and characteristics.
	(Lorentzen et al., 2017)	Symposium	-Historic development of fast charging points in Norway
	(Bąk & Makolska-Tenold, 2017)	Journal Article	-Number of charging stations and charging points
	(Mersky et al., 2016)	Journal Article	-Number of charging points
	(Springel, 2017)	Job Market Paper	-Number of charging stations, outlets, and their coordinates
	(Haugneland & Hauge, 2015)	Journal Article	-Number and type of charging points
	(Kvisle & Myklebust, 2013)	Symposium	-Entire Charging Station Database
	(Malinen et al., 2013)	Symposium	-Entire Charging Station Database
Electromaps	(Maza-Ortega et al., 2021)	Book Section	-Location and number of charging stations
	(Gómez-Mesino et al., 2020)	Conference Paper	-Total number of charging stations
	(Jordán et al., 2018a)	Conference Proceedings	-Total number of charging stations
	(Jordán et al., 2018b)	Conference Proceedings	-Total number of charging stations

Findings from Table 3 indicate that the above data sources have been widely used since the last decade in 11 countries with a primary focus on charging infrastructure location and size. Such a finding provides a certain degree of confidence that these data sources – after reviewing and scrutinizing – could form a reasonable base for city-city comparisons and city-specific analysis of charging locations' distribution along with associated city characteristics (e.g.,: population, ambient temperature, and congestion level).

3.3.3. Data extraction and spatial modeling

Data extraction followed two approaches: a) direct approach, and b) hybrid approach. The direct approach is based on fetching EVCI data directly from data sources' publishers or downloading it from their web portal. Afterwards, data filtration is introduced to include EVCI data within the city of study only. Examples of the data attributes provided by some sources are: station name, street address, city, ZIP, number of charging outlets, latitude, longitude…etc. On another side, when publicly available published data was that rare and only present as a navigation service, a hybrid approach is adopted relying on Electromaps, QuickOSM plugin, and manual tracking via Google Earth platform. As shown earlier in Fig. 8, after this step, all EVCI locations are geospatially modeled.

3.3.4. Data categorization, review, and quality check

Data wrangling showed a variety of charging locations density ranging from 1 to 230 locations in 1 km^2, which aroused curiosity about the level of charging infrastructure resembled by each data source. Extensive outreach efforts to the publishers of these data were exerted and the findings were quite dispersed. The data set selected from each source is scrutinized to have a consistent level of charging infrastructure, choosing the "charging pool" to be the most appropriate level of study. The reason for choosing the highest level of EVCI is the availability of international best practices and building codes for the determination of EVCI share from a facility space based on land uses' types. Moreover, the number and type of charging outlets would primarily depend on the capacity of the power grid and the EV model prevalent in a city (Lu et al., 2014) (MacDonald et al., 2021).

When examining the spatial locations of charging pools, some places were found to be off boundaries (e.g., in the water). These locations were further investigated by outreaching out to the data publishers and examining Google Maps platform. A correspondence from Electromaps data source stated that most of the locations on their map are generated by information from companies that manage the charging stations, and sometimes this information is not 100 % accurate. Consequently, the effort exerted in this research is structured as follows: locating inaccessible charging locations, searching for their correct location by facility name and/or address using Google Maps platform, and finally transferring these inaccessible charging locations into their correct position. It should be noted that these inaccessible locations represent only 0.24 % of the data points and are primarily found in China. Such effort was essential to ensure the integrity of the data inputs to be further used in the analysis.

As another level of scrutiny, Google Street View from Google Maps platform was used for data quality review. A random sample of 11 cities was taken proportionally to the city size, and as a function of the variety of charging infrastructure (e.g., parking lots, buildings, fuel stations, etc). The results indicated that in 95 % of the cases, EV charging locations were verified. Fig. 9 shows a sample of data quality review for city of Los Angeles.

4. EVCI multi-dimensional serviceability analysis

Disclaimer: The primary single data source for China cities "Electromaps" is used previously by other cities to study the location and the total number of charging stations. However, due to the limited publicly available published charging data for China cities, the analysis and conclusions should be carefully extrapolated to other cities. Despite the

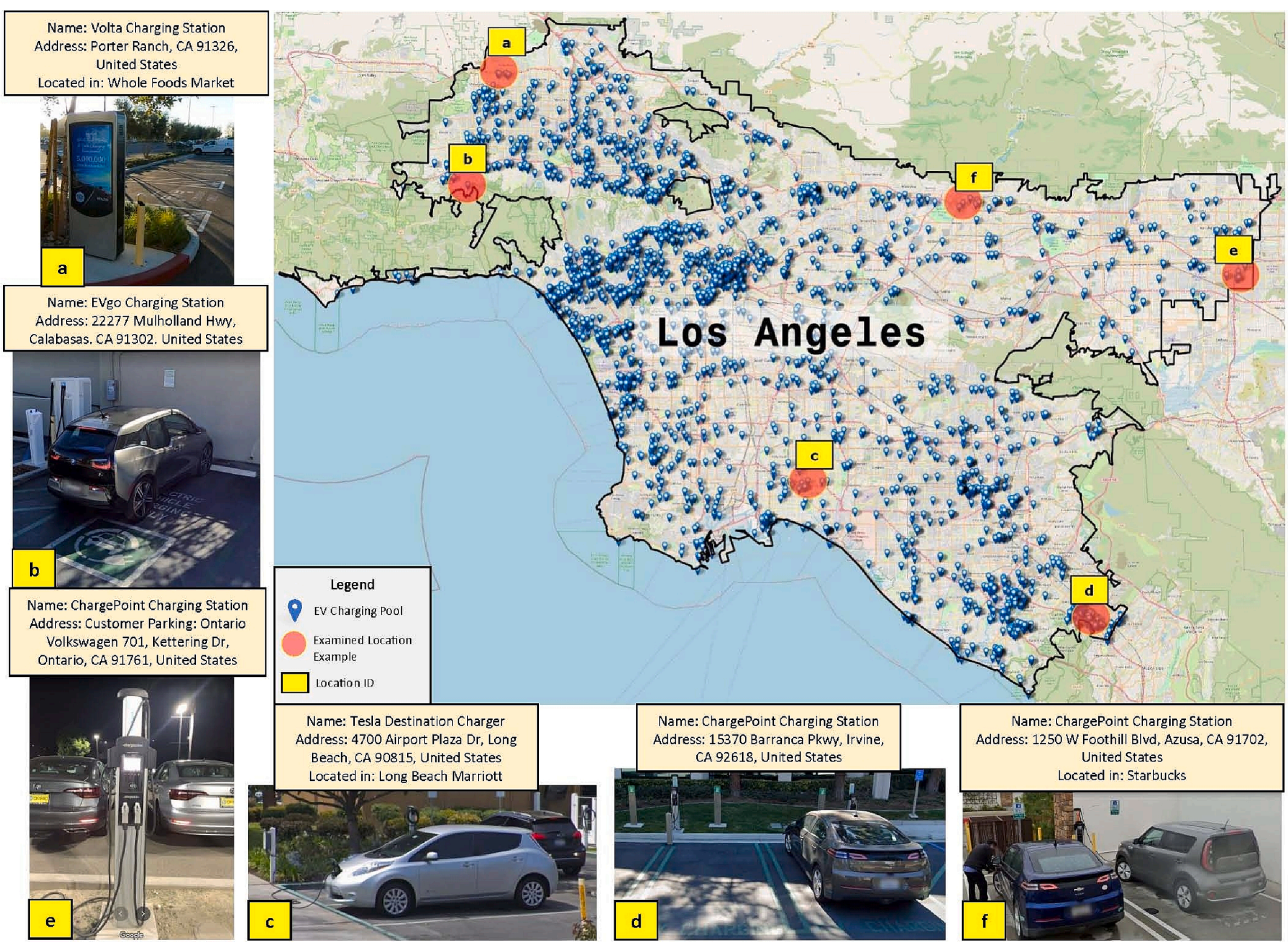


Fig. 9. Selected Data Quality Review for City of Los Angeles.

above facts, and due to the aggressive investment of China government in e-mobility (Hall et al., 2020), the former noted Chinese cities are included in the analysis for the sake of comprehensiveness.

4.1. Service coverage

4.1.1. City area share

The first question that could arise while planning EVCI for a city is the percentage of area to be covered with charging locations. This aroused the curiosity of this research to investigate the percentage coverage of EVCI as a function of the geographic distribution of the listed cities. As a first attempt, cities were spatially covered by 1 km^2 cells. Cells having one or more charging pools are defined as *"Covered Cells"*. The percentage of covered cells to the total number of cells covering the city is calculated to estimate the coverage index for this city.

Calculating a generic overall indicator representing % coverage within a city suffered from a bias to cities with more developed areas as compared to cities with large areas of water bodies, forests, etc. For example, though Oslo has reached the late majority as per the market categories of consumer (Fig. 7), it had a low coverage index of 23.56 %, unlike Amsterdam which is at the beginning of the early majority phase (less mature market compared to Oslo) but had a higher coverage index of 60.7 %. When observing the geographical features of both cities, it was clear that a considerable portion of Oslo is forests (mainly in the north), with charging locations covering the majority of populated areas (middle area and south-west). Amsterdam, on the other side, has a dominant populous area all around the city, with charging locations covering the majority of those populated areas, and green areas concentrated in the north-east. This accentuated the need for revising the coverage index to take into consideration the share of accessible areas among cities and how well covered are they.

A revised coverage index is defined by taking the denominator as the number of cells covering accessible areas Eq. (2). Fig. 10 shows accessible areas for cities of study versus inaccessible areas. China cities appear to have a clear extent of unpopulated areas followed by some European cities and finally come the U.S. cities with almost 100 % populated areas. Moreover, Fig. 10 also reveals the size variations among cities of study (examined through the size of 1 km^2 cell), with China cities being the largest, followed by the U.S. cities, and finally come cities of Europe.

$$\textit{Accessible Areas Coverage Index } (AA-CI)\% = \frac{\textit{Number of Covered Cells}}{\textit{Number of Cells Covering Accessible Areas}} * 100 \quad (2)$$

4.1.1.1. City-city comparison. The results of the revised coverage index are shown in Fig. 11a where Mega EV cities are plotted in an order representing their sales level, whose increase represents an increase in the cumulative sales of EVs from (2010–19). From a city-city viewpoint, the outcomes of *AA-CI* indicated three distinct patterns; 1) mostly-covered cities; green area, [50–100] %, mainly in Europe, 2) medium-covered cities; yellow area, [10–50) %, in the U.S. and Europe, and 3) low-covered cities; red area, [0–10) %, with all China and Japan cities as well as one U.S. city (New York). The mostly covered cities exhibited an average coverage of 57.28 % with a minimum of 49.61 % in Oslo and a

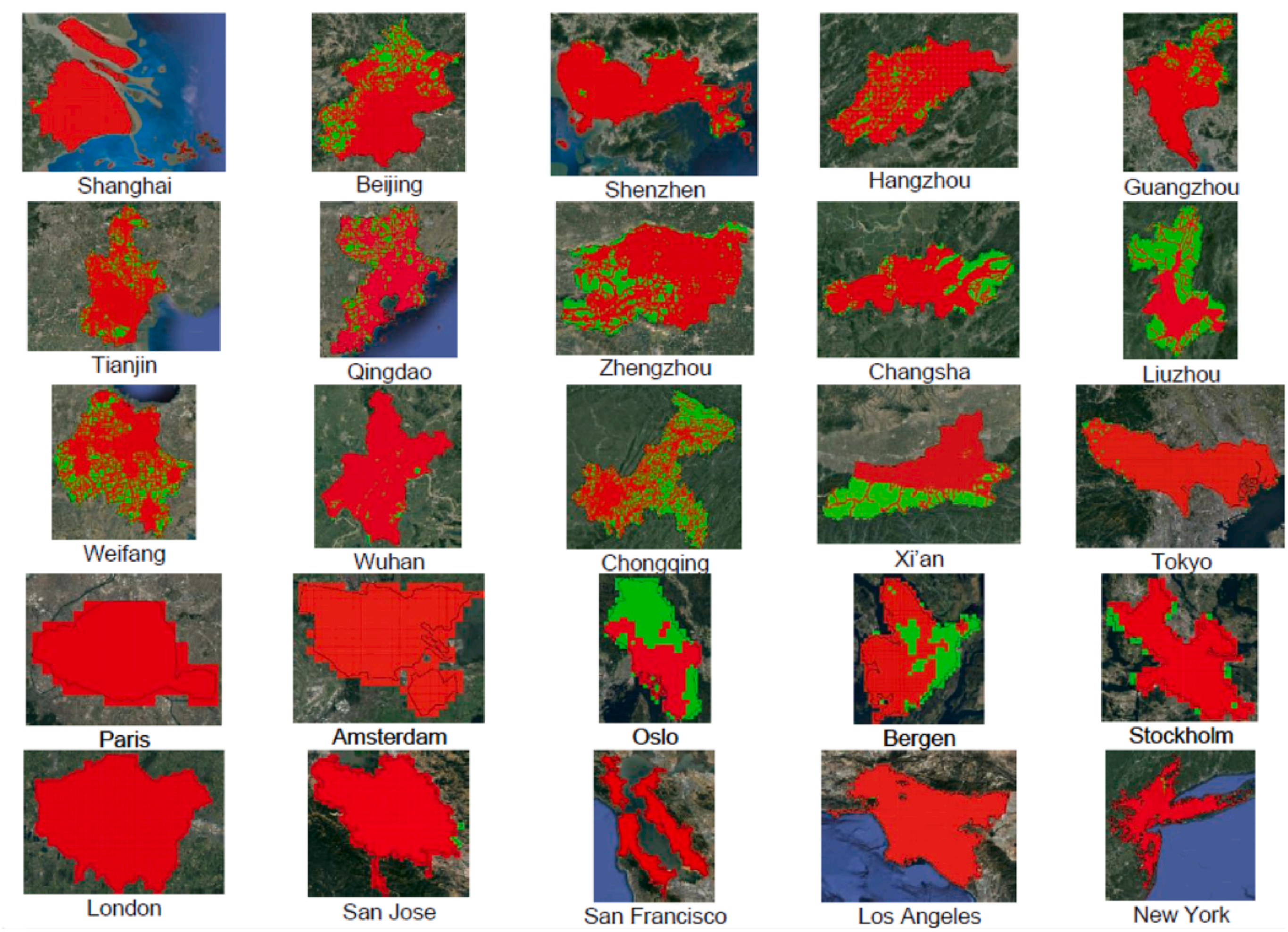


Fig. 10. Accessible Areas (red) vs Inaccessible Areas (green) for Mega EV Cities.

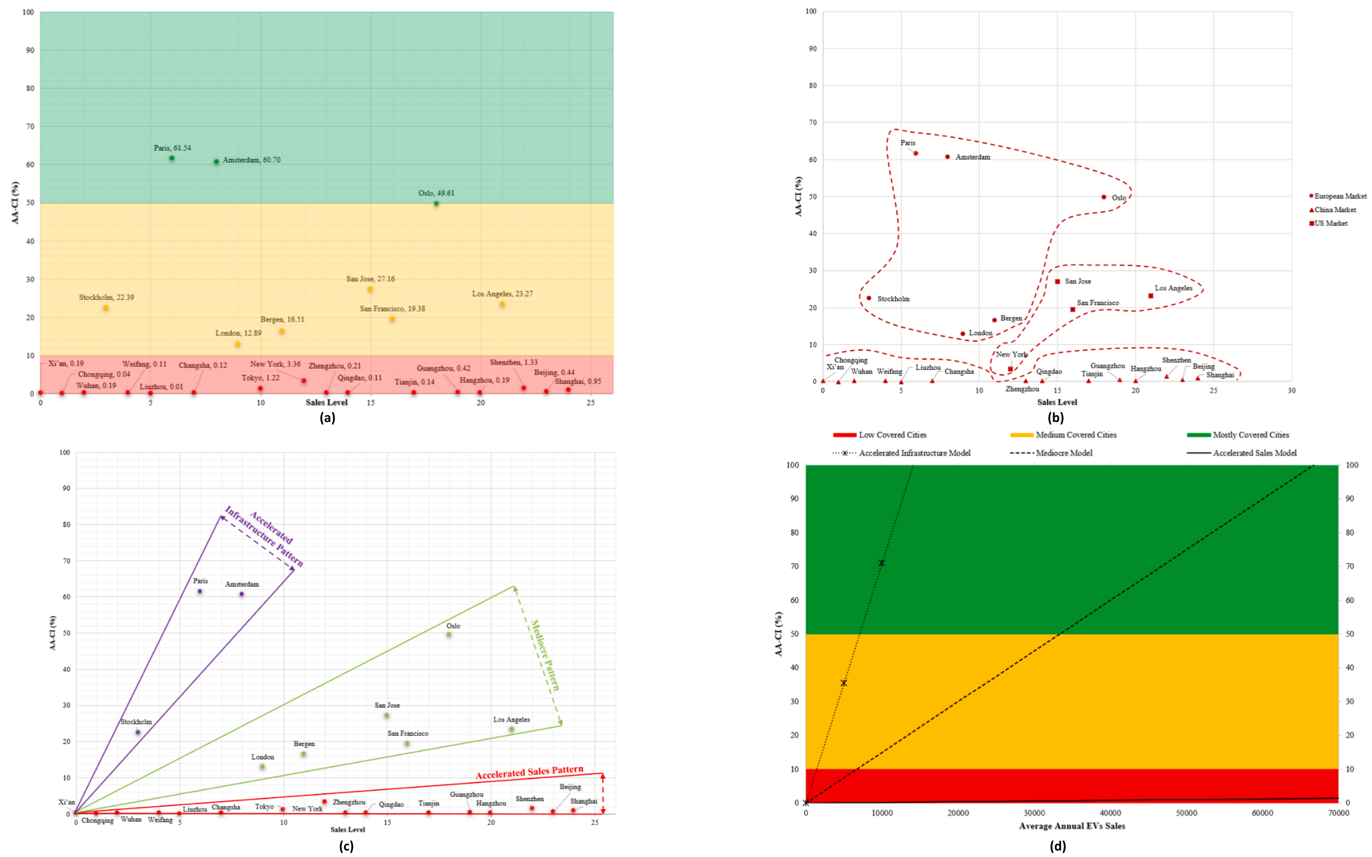


Fig. 11. EVCI Accessible Areas Coverage Index (AA-CI) for Mega EV Cities. a) City-City Comparison, b) Market Patterns, c) Worldwide Trends, d) Regressed Multi-dimensional Model.

maximum of 61.54 % in Paris. The medium-covered cities exhibited an average of 20.27 % with a minimum of 12.89 % in London and a maximum of 27.16 % in San Jose. Finally, the low-covered cities exhibited an average of 0.56 % with a minimum of 0.01 % in Liuzhou and a maximum of 3.36 % in New York.

4.1.1.2. Market patterns. Restructuring Fig. 11a to be viewed from a market perspective, Fig. 11b exhibits three patterns: the European market with a relatively compact pattern concerning cumulative EVs sales (2010–19) and a flat pattern concerning EVCI city area coverage. On the other side, the Chinese market exhibits a flat pattern concerning EVs cumulative sales and a tight one concerning EVCI city area coverage. In the middle between these two markets, the U.S. market shows a modest performance. Considering the 2019 market categories of consumer shown earlier in Fig. 7, the European market has shown on average the highest maturity level followed by the Chinese market, and finally comes the U.S. market.

4.1.1.3. Overall worldwide trends. From a worldwide perspective, Fig. 11a can be viewed from another context as configured in Fig. 11c. Three distinct patterns have been observed; 1) accelerated infrastructure pattern; where cities have intensively focused on attaining a wide EVCI coverage for populated areas though low demand of EVs (mostly in Europe), 2) accelerated sales pattern; where cities tended to intensively sell as many EVs as possible with a minimum coverage of EVCI (mostly in China), and 3) mediocre pattern; where there was a balanced performance between EVs sales and EVCI coverage (mostly in the U.S. and Europe).

To have a perception of the effect of EVs sales on each pattern, average annual sales of EVs have been calculated by dividing the cumulative sales (2010–19) by its period. This was done limited by data availability for the annual growth of EVs sales for each city and to maintain the rank of each city the same as the cumulative sales, so as not to bias the observed patterns. Afterwards, average annual EVs sales have been plotted against *AA-CI* and data were fitted using linear regression.[6] A multi-dimensional model relating average annual EVs sales, city-city results, and worldwide trends is thus developed (Fig. 11d). This model shall represent a step for EVCI planning in cities based on: 1) average annual EVs sales, 2) city infrastructure coverage target (mostly covered zone, medium-covered zone, or low-covered zone), and 3) demand-supply e-mobility anticipated model (accelerated infrastructure model; $y = 0.0071x$ ($R^2 = 0.8988$), accelerated sales model; $y = 2E\text{-}05x$ ($R^2 = 0.7803$), or mediocre model; $y = 0.0015x$ ($R^2 = 0.7277$)). It should be noted that the accelerated infrastructure model is valid for EV sales $\leq$14,084 and the mediocre model for EV sales $\leq$66,666. Though the R^2 of the accelerated sales model has reached 0.7803, the structure of the deduced model is near to be flat, which represents a very low correlation. This is assumed to be related to the way China cities are spreading their EVCI locations. The assumption is that maybe China cities are installing a few locations for EVCI but with high capacity (large number of charging stations within). However, limited by data availability, it cannot be verified in this research.

Despite the fact that Fig. 11d provides a very general view of EVs sales vs EVCI coverage, it can form a starting point for governments starting in a green field to plan for their EVCI. In such a case, planners

[6] New York and Tokyo cities' data points have been eliminated from the accelerated sales model as outliers. This has enhanced the R^2 of the fitted model by 177%. It should be noted that all models have been forced to have a "0" intercept with the y-axis, assuming that there is no EVCI coverage for zero sales of EVs (limited by data availability).

can use this model in one of two ways; determine the average annual EVs sales accommodated by specified %coverage of EVCI and vice versa.

4.1.2. City demographic share

The number of charging pools (CPs) per million population for cities of study was plotted against the sales level of each city, resembling an approximate relationship between supply and demand. In Fig. 12, cities are further color-coded with respect to TomTom 2020 city size classification by population. The results show that most mega cities lie in the bottom border of CPs/million population regardless of their sales level. On the contrary, large cities are taking the lead with a maximum of 1402.12 CPs/million population in Amsterdam. This high value in Amsterdam can be explained by the type of parking citizens have access to, where most of them park their vehicles on-street not in private parking (Fishbone et al., 2017). This has also been observed when performing the spatial scrutiny of charging infrastructure data for city of Amsterdam. Another example of high values for CPs/million population are cities of California State – home to ½ of EVs in the U.S. – (San Francisco and San Jose), where 83 % of EV drivers use home charging (Hall & Lutsey, 2020b), thus might be explaining these high values.

4.1.3. Effect of traffic conditions on EVCI area coverage

In Fig. 13, TomTom 2020 congestion level was plotted against *AA-CI* and a polynomial 2nd degree model was used to fit the data points available. The decision of the fitted model is an attempt by this research to explore whether a similar or complementary trend to what (Fiori et al., 2019) have concluded, exists between traffic conditions and EVCI coverage in Mega EV cities. The results show a constant *AA-CI* till 20 % congestion level then a decrease occurs as the congestion level increases. This is compatible with the outcomes expected, where, as the energy consumption increases at higher speeds (low congestion levels), it was expected to have a higher value of *AA-CI* to accommodate for range anxiety and vice versa. However, the low R^2 value of the fitted model indicates that this model is weak to be used for predicting the value of *AA-CI* based on TomTom congestion level.

4.1.4. Effect of prevalent degree of electrification on EVCI area coverage

From Fig. 6, cities have been classified based on the prevalent EV type, then Fig. 11a is modified to be color-coded based on this classification as shown in Fig. 14. The results show that all leading cities concerning *AA-CI* (lie in the mostly-covered zone) have BEV as a dominant type and generally BEV cities are distributed among all coverage zones (mostly-covered, medium-covered, and low-covered). On the other hand, PHEV cities are distributed between the low-covered and medium-covered zones. There was no clear evidence that Mega EV cities have considered this factor while planning for EVCI service coverage.

4.2. Charging pools density distribution in 1 km^2 covered cells

The previous analysis provided city-wide insights when it comes to coverage index spatially represented by 1 km^2 cells. Yet, the density of charging locations within a sized area limit for a city poses another level of analysis that is useful for EVCI planning. Therefore, the density of charging pools in the 1 km^2 covered cells has been calculated – including its frequency – for Mega EV cities as shown in Fig. 15a. The majority of EV capitals have shown a tendency to locate 1 charging pool/1 km^2 covered cell. Moreover, some cities were compact in their distribution (mostly in China and Japan) (Fig. 15b), whereas other cities tended to have a more elongated distribution of charging pools (like Amsterdam) (Fig. 15c). This indicates that some cells have been supplied with a large number of charging locations forming "hub-like" areas, while others have quite few charging locations.

4.2.1. In relation to scale-free networks

When examining the distribution of the number of charging pools/1 km^2 covered cells among global EV markets as shown in Fig. 16, a consistent power-law distribution has spread among markets and consequently worldwide. This proves that the global distribution of EVCI is demand-driven with a scale-free network structure. Fig. 16 shows that global markets have an ascending trend for $\in$ as follows: the European market with the smallest value of 1.063, followed by the U.S. market with 1.969, and finally comes the Chinese market with 2.988. This shows that the European market has an aristocratic pattern; where the variation in the number of charging pools/1 km^2 cells is large among covered cells, with some cells being favored with a large number of charging pools whereas others have few of them. On the other hand, the Chinese market has an egalitarian pattern; indicating a homogenous low

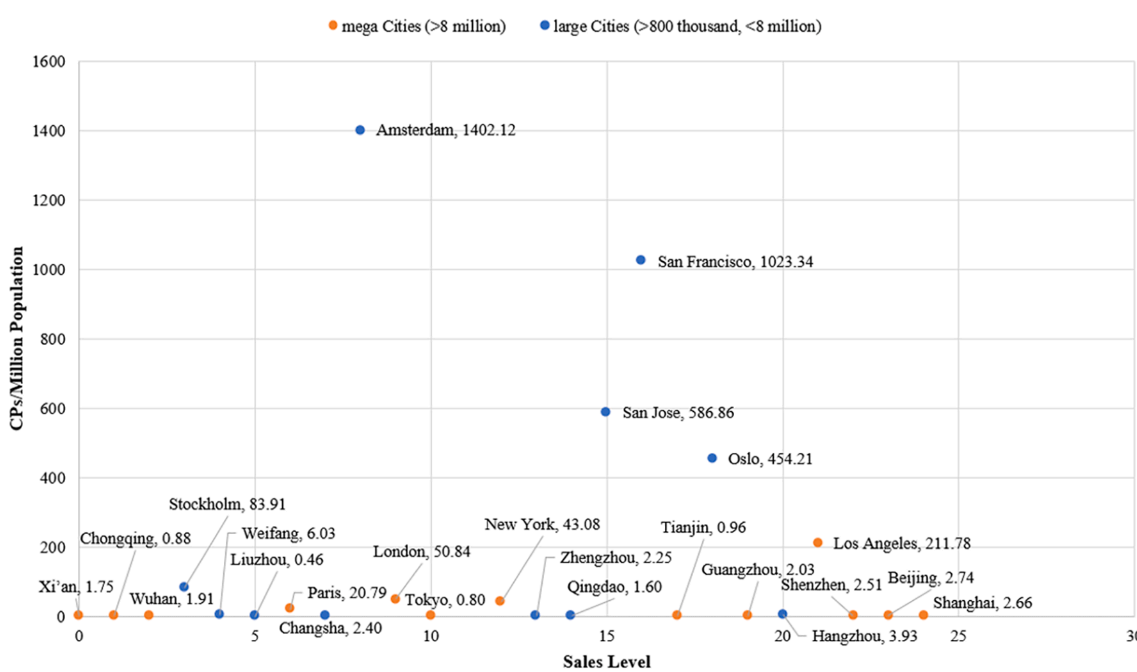


Fig. 12. Charging Pools (CPs) per Million Population for Selected Mega EV Cities.

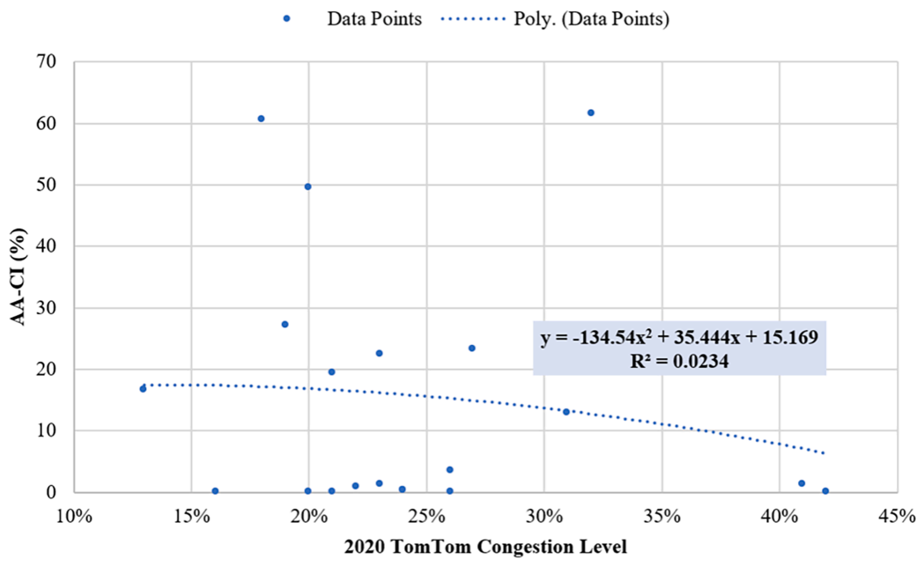


Fig. 13. TomTom Congestion Level (2020) vs AA-CI for Selected Mega EV Cities.

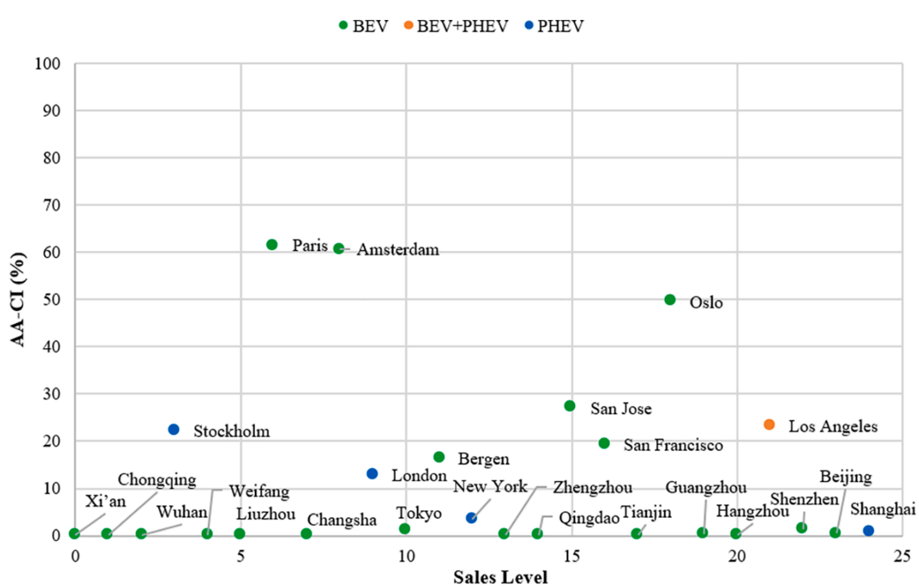


Fig. 14. Effect of Prevalent Degree of Electrification on AA-CI for Mega EV Cities.

density of charging pools/1 km^2 cells among all covered cells. For the U. S. market, it has an intermediate pattern between the European and the Chinese market. Finally, for the worldwide model, Fig. 16 shows that it has an ϵ value of 1.523 lying in between the European and the U.S. market.

4.2.2. *In relation to settlement pattern of a city*

Fig. 17 shows high-density zones of EV charging locations in populated areas of the European and U.S. cities. Three distinct shapes were observed (red areas): centered, linear, and scattered. Some cities had centered high-density EVCI zones like Amsterdam, Oslo, San Jose, and New York, while other cities had linear zones like Paris, London, and San Francisco. The scattered zones were observed in Bergen and Los Angeles. Finally, Stockholm city had a small-centered zone in the east. The structure of these zones is much like the settlement pattern for each city. Mega EV cities were classified based on their urban areas' connectivity to be nucleated (N), linear (L), and dispersed (D). As shown in Fig. 17, most nucleated cities have centered high-density EVCI zones except for Los Angeles and Stockholm, all linear cities have linear zones, and all dispersed cities have scattered zones.

In summary, *"EVCI is demand-driven with a scale-free network structure. High-density zones of EVCI are developed based on the shape of populated areas, restrained by the surrounding topography."*

4.3. *Service radius*

Two measures have been used to represent EVCI service radius: one representing the centrality[7] of EVCI in a city; as, if one randomly points out a location on the map of this city, by how many kilometers radius it is expected to find a charging location. The other measure represents the proximity of EVCI; as, if one is at an existing charging location, it is expected to find the next charging location within how many kilometers.

[7] *"Centrality"* terminology is inspired from the concept of *"Closeness Centrality"* adopted by (Jayaweera et al., 2017), where they defined it as the average shortest path distance between a node and all other nodes reachable from it.

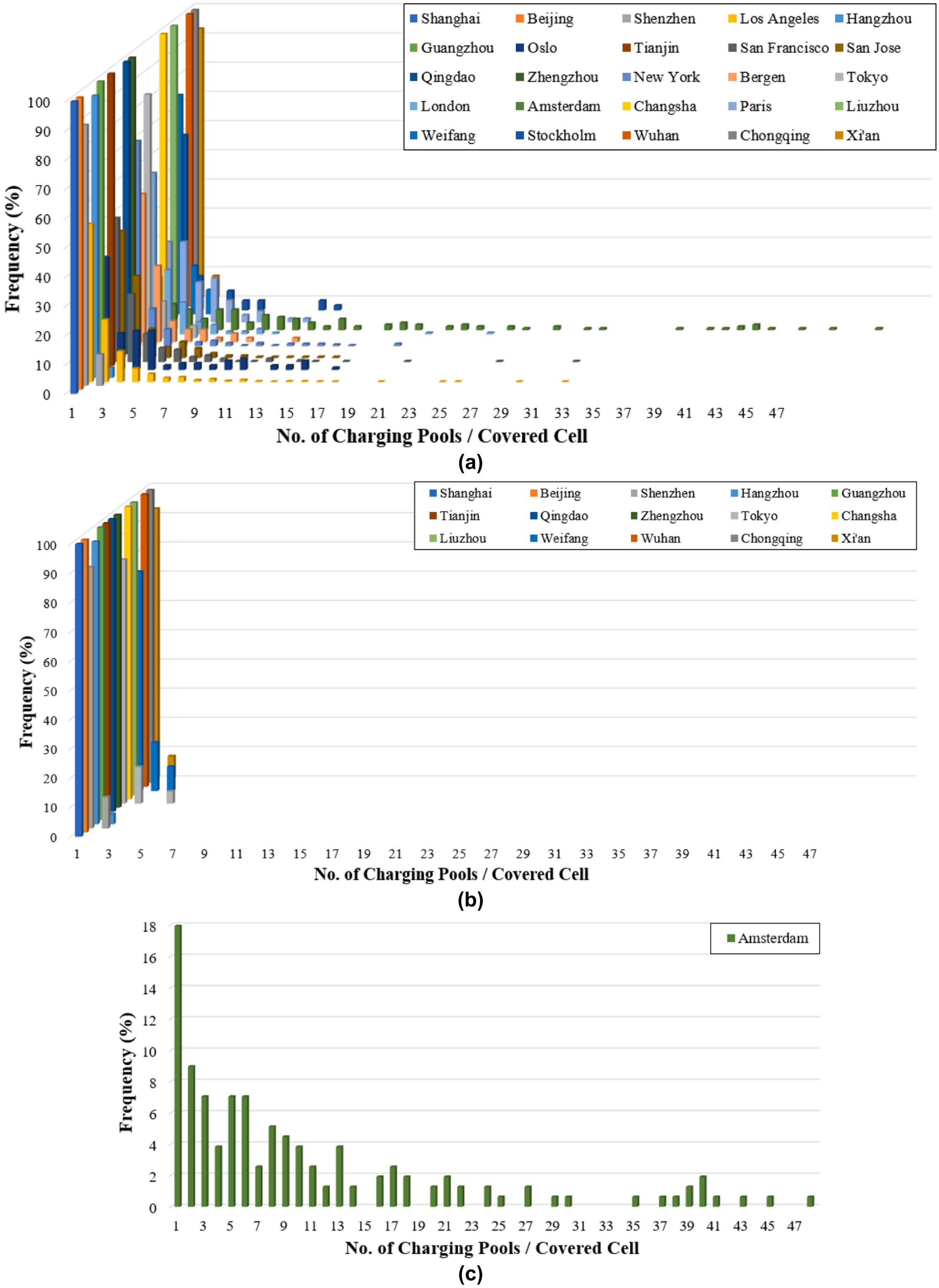


Fig. 15. Density Distribution of Charging Pools in 1 km^2 Covered Cell. a) Mega EV Cities, b) China and Japan Cities, c) City of Amsterdam.

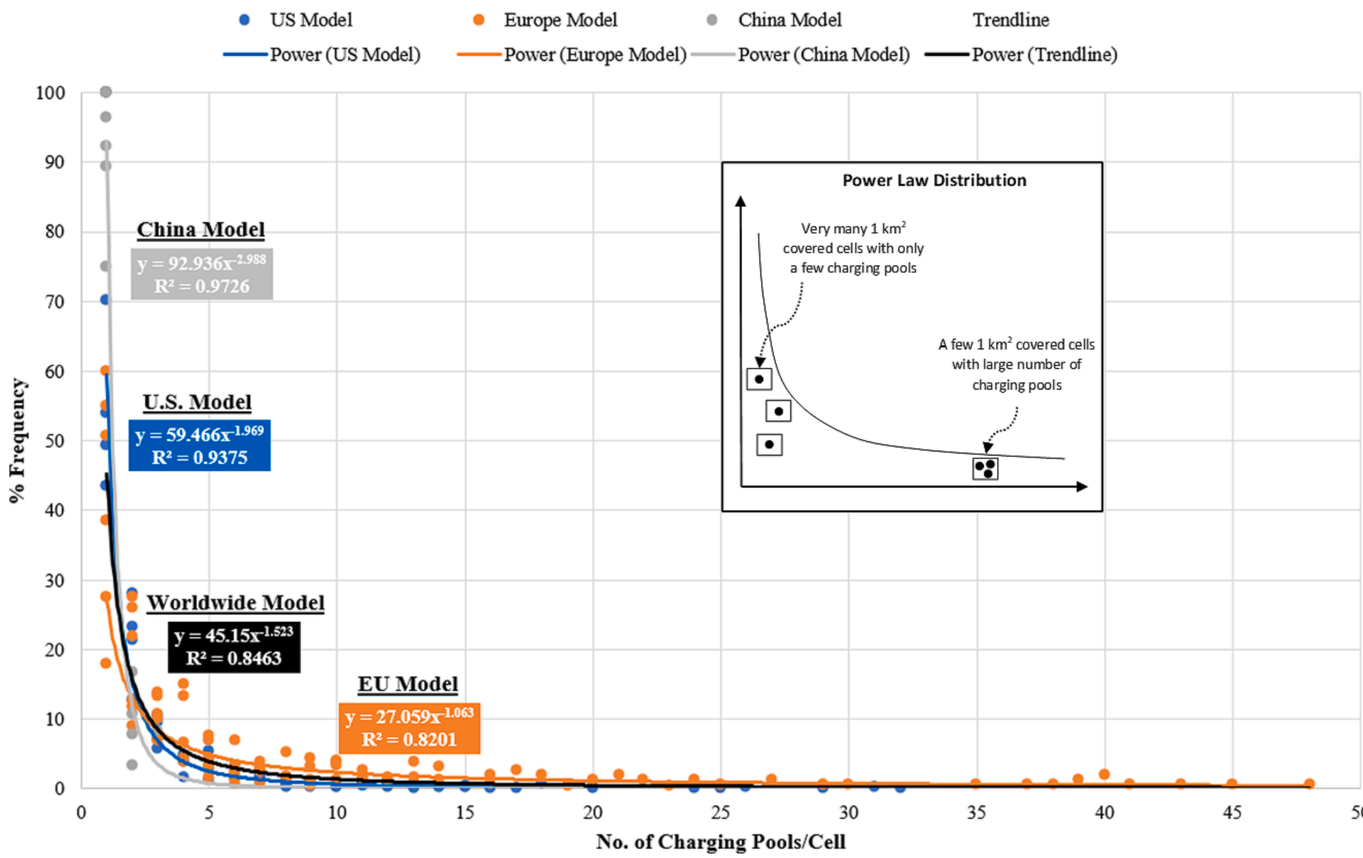


Fig. 16. The analogy between demand-driven networks with a power-law distribution and density distribution of charging pools in 1 km² covered cell in Mega EV cities.

4.3.1. The measure of centrality

This measure is determined by firstly calculating a summary distance matrix between all charging locations in a city – using QGIS – having the average spacing from each charging location to all other locations. It should be noted that all distances are straight-line distances not considering the road network layout. Fig. 18 shows box and whisker plot for the distribution of average spacings between charging pools in selected Mega EV cities. The results show that most of these distributions are not normally distributed, thus the more reliable measure of data centrality would be the median (Q2). Median values are determined for each city; thus, the Mid Average Spacing (MAS) measure for Mega EV cities is determined (Fig. 19).

As shown in Fig. 19, the results indicated three distinct zones: 1) highest connectivity [0–10) km, 2) intermediate connectivity [10–25) km, and 3) lowest connectivity ≥25 km. For the high connectivity zone, if one randomly points out a location on any map for cities therein, it is expected to find a charging location within 10 km radius. For the intermediate connectivity zone, it would be between 10 and 25 km. And finally, for the lowest connectivity zone, it would be >25 km. The term "connectivity" used is inspired from (Derrible, 2010), where the more the network is centralized, the more connectivity it provides.

Interestingly, though the summary distance matrix calculated for each city is based on straight-line distances (not considering the road network), the effect of road network topology has emerged in the results of MAS. The majority of cities in the highest connectivity zone are classified as "Grid + Radial", all cities in the lowest connectivity zone are classified as pure "Grid", and finally, cities in the intermediate connectivity zone are a combination between pure "Grid" cities and "Grid + Radial" cities (Fig. 19 and Table 4).

From a market perspective, most of the European cities lie in the highest connectivity zone, most of China cities lie in the intermediate connectivity zone, and finally, the U.S. cities are distributed among the intermediate and low connectivity zones. This measure is anticipated to be of due importance considering the range anxiety of ***highway driving***.

4.3.2. The measure of proximity

This measure is determined by firstly calculating a summary distance matrix between all charging locations in a city – using QGIS – having the minimum spacing from each charging location to all other locations. It should be noted that all distances are straight-line distances not considering the road network layout. Fig. 20 shows box and whisker plot for the distribution of minimum spacings between charging pools in selected Mega EV cities. The results show that most of these distributions are not normally distributed, thus the more reliable measure of data centrality would be the median (Q2). Median values are determined for each city; thus, the Mid Minimum Spacing (MMS) measure is determined for Mega EV cities (Fig. 21).

As shown in Fig. 21, the results indicated three distinct zones: 1)

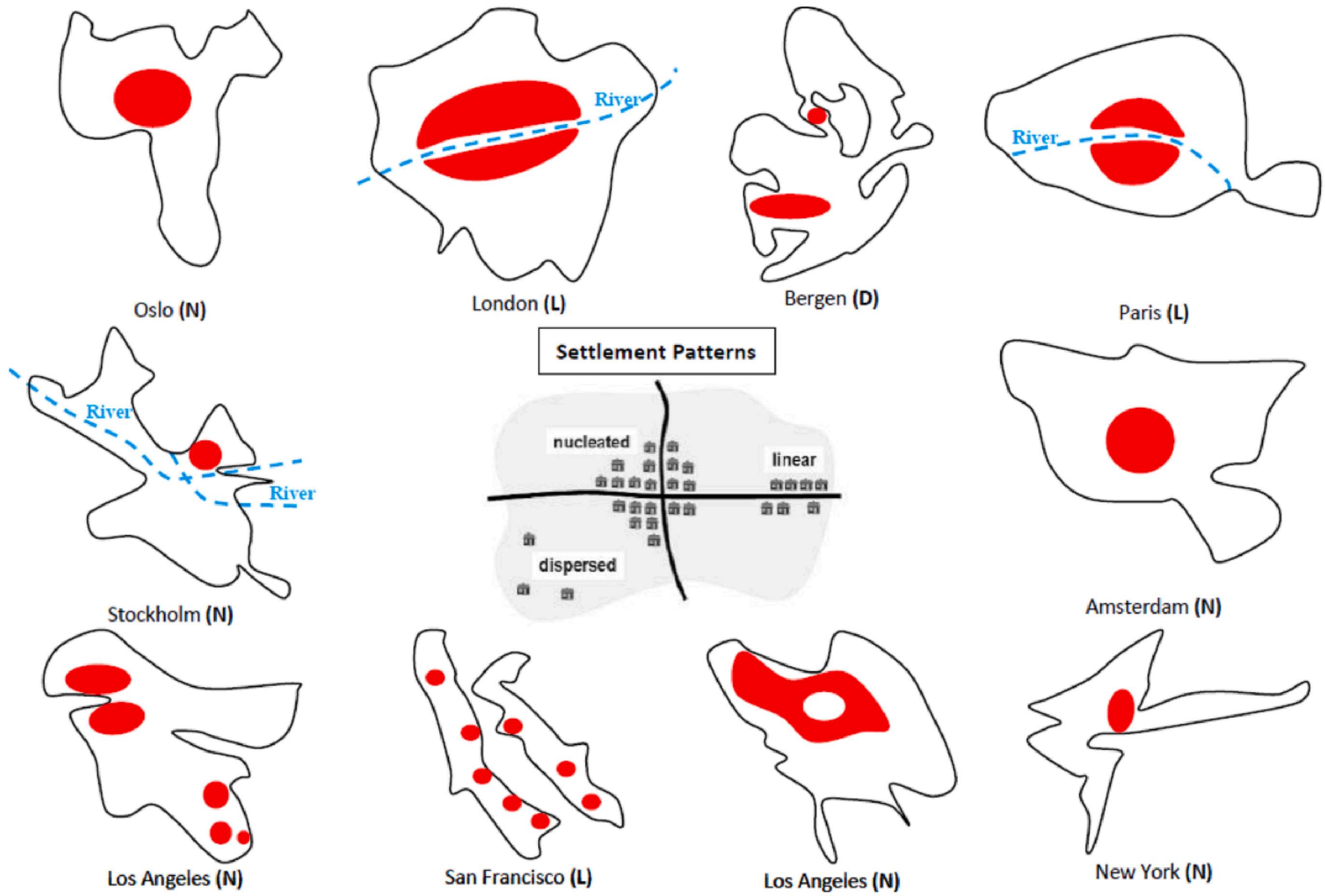


Fig. 17. The Relationship between Urban Areas Settlement Patterns and High-Density Zones of EV Charging Locations (red areas) in Populated Areas of the European and U.S. Cities.

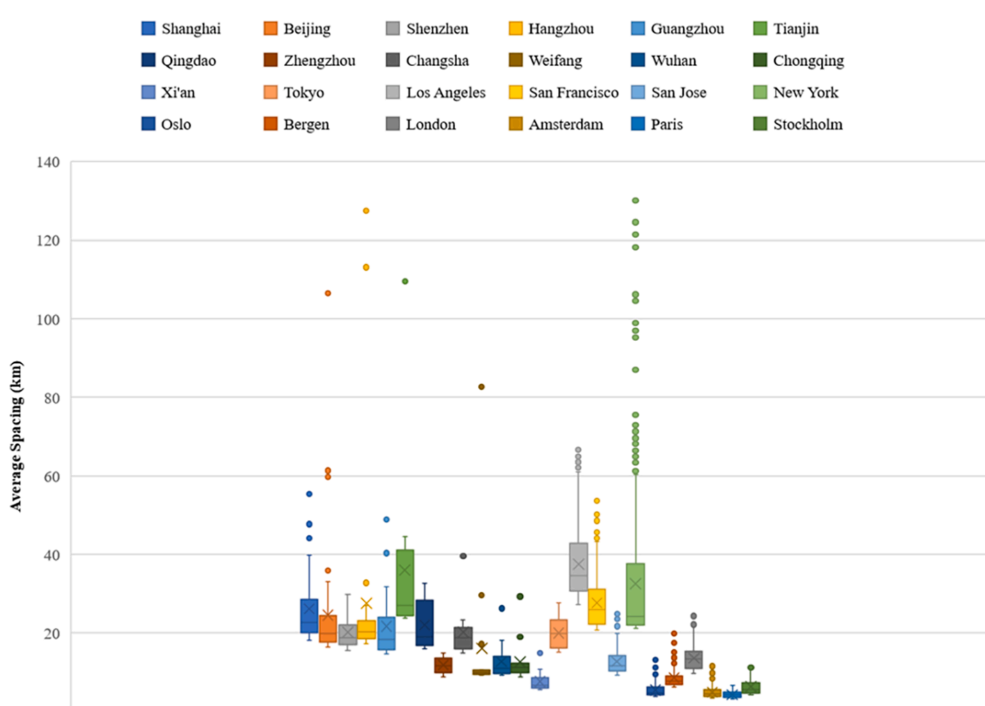


Fig. 18. Box & Whisker Plot for Average Spacings between Charging Pools in Selected Mega EV Cities.

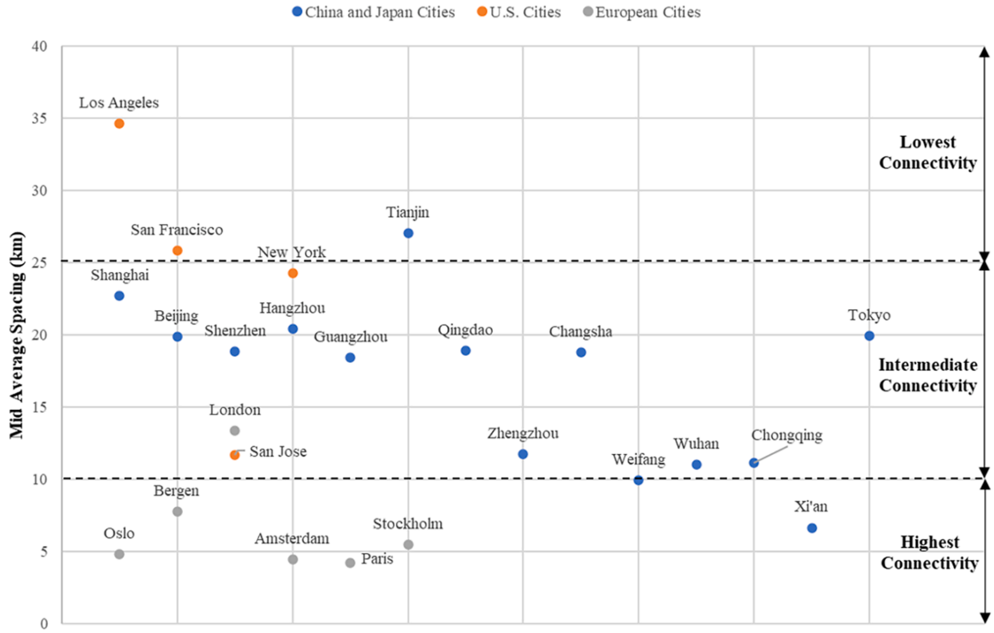
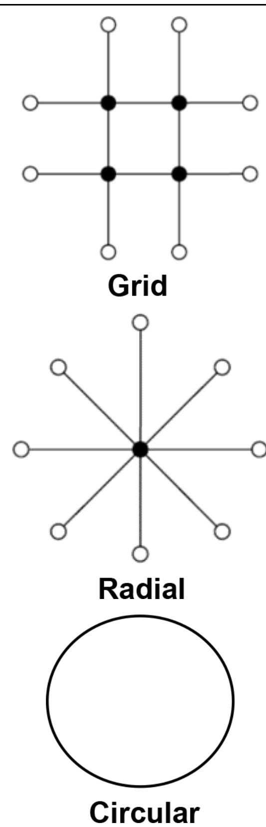


Fig. 19. Mid Average Spacing (MAS) Measure in Selected Mega EV Cities.

Table 4
Road Network Topology Classification for Selected Mega EV Cities.

City	Topology Classification	Abstract Illustration
Shanghai	Grid	
Beijing	Grid + Radial + Circular	
Shenzhen	Grid	
Los Angeles	Grid	
Hangzhou	Grid	
Guangzhou	Grid	
Oslo	Grid + Radial	
Tianjin	Grid	
San Francisco	Grid	
San Jose	Grid	
Qingdao	Grid	
Zhengzhou	Grid	
New York	Grid	
Amsterdam	Grid + Radial + Circular	
Changsha	Grid	
Bergen	Grid + Radial	
Tokyo	Grid + Radial	
London	Grid + Radial	
Paris	Grid + Radial	
Weifang	Grid + Radial	
Stockholm	Grid + Radial	
Wuhan	Grid + Radial	
Chongqing	Grid + Radial	
Xi'an	Grid + Radial + Circular	

highest proximity [0–1) km with all the European and U.S. cities, 2) intermediate proximity [1–5) km with most of China cities, and 3) lowest proximity ≥5 km having Qingdao city. For the highest proximity zone, if one is at an existing charging location for any city therein, it is expected to find the next charging location within 1 km. For the intermediate proximity zone, it would be within 1–5 km. Finally, for the lowest proximity zone, it would be >5 km. This measure is anticipated to be of due importance considering the range anxiety of ***city driving***. Moreover, it can be integrated with smart charging applications to plan for the nearest charging trip based on the available capacity at different charging pools.

4.3.3. *Effect of traffic conditions on EVCI service radius*

As mentioned earlier, EVs exhaust less energy in congested conditions than free-flow conditions (Fiori et al., 2019). For a second trial, this research has explored the rationale of the quadratic pattern deduced by (Fiori et al., 2019), between charging pools' spacings and traffic conditions. TomTom 2020 congestion level is plotted for each city versus MAS and MMS respectively. A 2nd degree polynomial model is used to fit the available data points.

For MAS, Fig. 22a shows that there is an inverted U-shaped pattern between MAS and TomTom congestion level, with no clear justification for having the MAS decreases again approximately after 30 % congestion level. For MMS, Fig. 22b shows that there is an increasing pattern for the value of MMS as the congestion level increases reaching a constant spacing at 30 % congestion level. The results of MMS are compatible with the outcomes expected, where, as the energy consumption increases at higher speeds (low congestion levels), it was expected to have smaller spacings between charging pools to accommodate for range anxiety and vice versa. However, the low R^2 value of the fitted models indicates that these models are weak to be used for predicting the value of MAS or MMS based on TomTom congestion level.

4.3.4. *Effect of prevalent degree of electrification on EVCI service radius*

Fig. 19 and Fig. 21 are modified so that cities are color-coded with respect to the prevalent EV type (BEV, PHEV, or an equal combination) (Fig. 23). Fig. 23a shows that BEV cities are distributed among the three connectivity zones, with most of them in the intermediate connectivity zone. Furthermore, PHEV cities are distributed among the high and intermediate connectivity zones, with most of them also in the intermediate connectivity zone. Fig. 23b shows that BEV cities are distributed among the three proximity zones. Moreover, PHEV cities are distributed among the high and intermediate proximity zones with most of them in the high proximity zone. There is no clear evidence that Mega EV cities

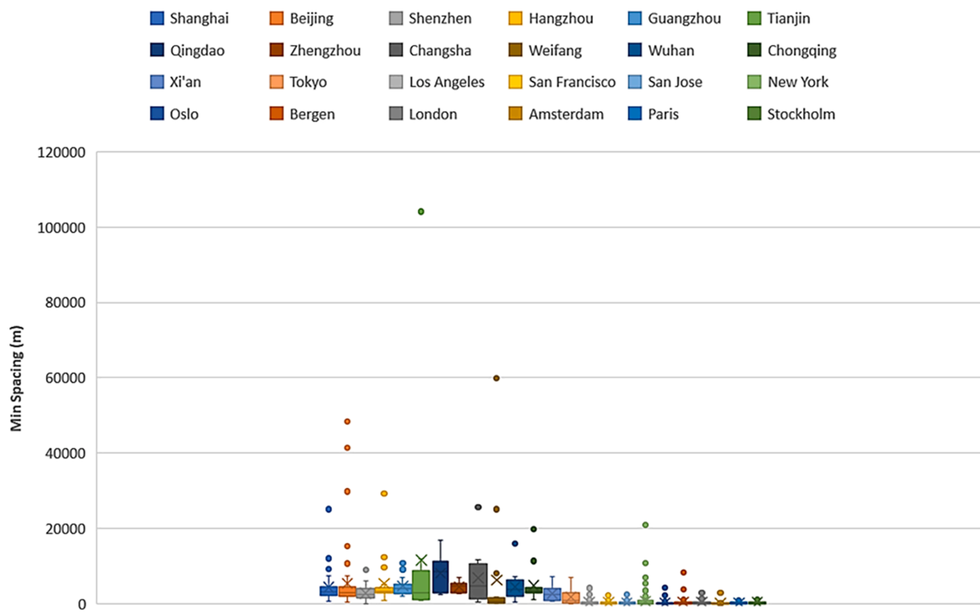


Fig. 20. Box & Whisker Plot for Minimum Spacings between Charging Pools in Selected Mega EV Cities.

have considered this factor while planning for the service radius of EVCI.

4.3.5. Effect of ambient temperature on EVCI service radius

This research has investigated whether a complementary pattern, to what was deduced by (K. Liu et al., 2018), exists between ambient temperature and spacings between charging pools in Mega EV cities. The average daily high and low temperatures in hot/warm and cold/cool seasons are plotted against MAS and MMS respectively. A third-degree polynomial model is then used to fit the available data points (Fig. 24). The results for MAS and MMS didn't comply with the expected outcomes (purple model), where an inverted U-shaped pattern was expected to resemble high values of energy consumption needing more charging pools to accommodate for range anxiety (i.e., less spacings). Moreover, the low R^2 value of the fitted models indicates that these models are weak to be used for predicting the value of MAS or MMS based on the ambient temperature data. It should be noted that cities of scope didn't have the characteristics of extreme hot temperatures like in Saudi Arabia, thus may be affecting the patterns deduced.

4.4. EVCI evaluation metrics: Cities' different levels of EVCI distribution

(Hall et al., 2020) have shown the availability of public charging infrastructure at the end of 2019 in top EV markets using three metrics; the absolute number of public chargers, the number of public chargers per million population, and the number of electric passenger vehicles per public charger (Fig. 25). (Hall et al., 2020) have declared that the results – limited by the data availability and considering small inconsistencies of data sources across markets – have shown an evident pattern for the first and second metrics as follows: 1) China cities possess the largest absolute public chargers' numbers, and 2) Shenzhen is the

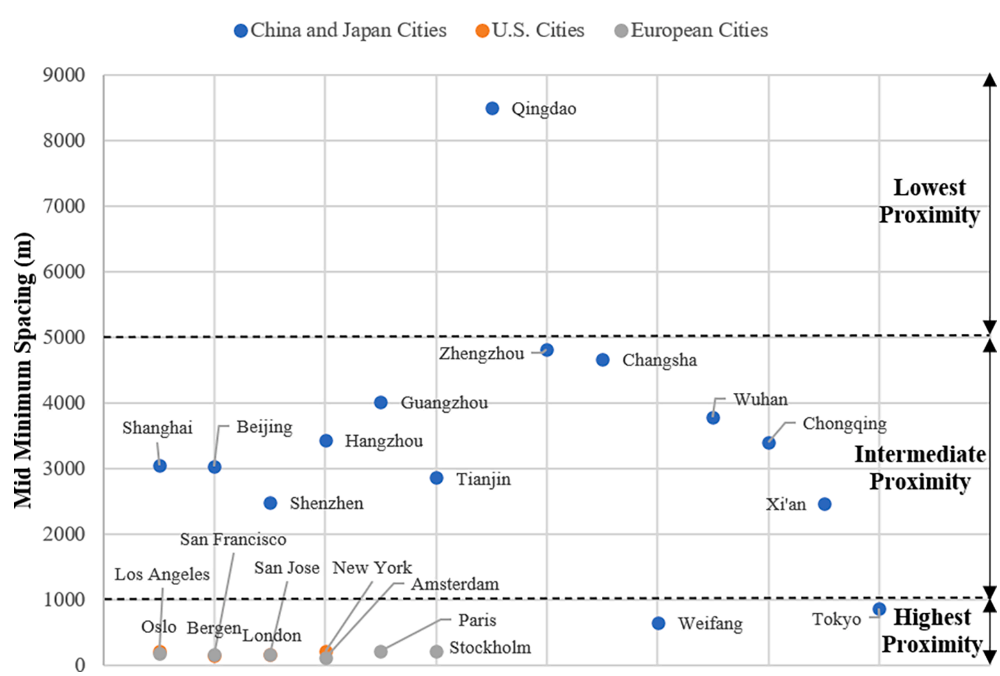


Fig. 21. Mid Minimum Spacing (MMS) Measure in Selected Mega EV Cities.

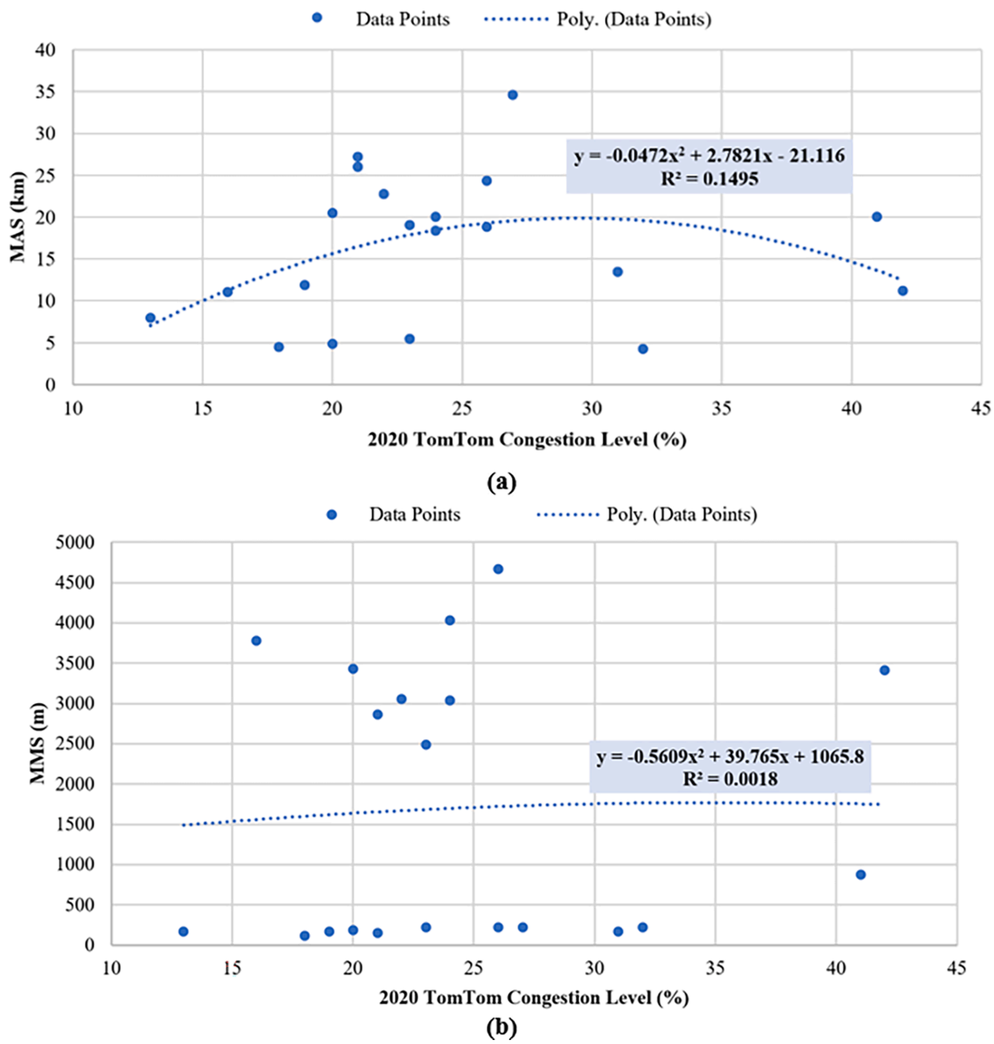


Fig. 22. Effect of Traffic Conditions on the Service Radius of EVCI in Selected Mega EV Cities. a) TomTom 2020 Congestion Level vs MAS of Charging Pools, b) TomTom 2020 Congestion Level vs MMS of Charging Pools

forerunner followed by Amsterdam and Oslo considering the number of public chargers per million population. On the other side, the third metric has no clear pattern.

Having the Chinese market the highest number of public chargers compared to Europe, the U.S., and Japan can be explained by the type of EVCI incentives adopted by the cities in those countries. Table 5 shows a summary of EVCI incentives in Mega EV cities with respect to two types: public and private charging. The Chinese cities show an intensified focus on public EVCI incentives with no endeavors in private charging except for city of Hangzhou. On the other hand, all the European and U.S. cities promote private charging, with Amsterdam, Stockholm, Los Angeles, San Francisco, and San Jose making their way out through both types of charging infrastructure.

When comparing charging infrastructure performance, cities should realize that there is no "one-size-fits-all". Local characteristics like housing type, vehicle mix, typical driving and commuting patterns, as well as the amount of DC fast chargers, differ from one city to the other. Therefore, these metrics should be considered as approximate general guidelines (Hall & Lutsey, 2020b). However, the three prementioned charging infrastructure evaluation metrics combined are shedding the light on cities' progress, targets, and planning as will be described in the following subsections.

4.4.1. *Optimal charging infrastructure: The case of Oslo*

Table 5 shows that city of Oslo's EVCI incentives are towards private charging, which may explain why it has a fewer number of public chargers than Beijing (Fig. 25), as the latter's focus is towards public charging. The dominant EV type for both cities is BEV (Fig. 6), which indicates that they need the same characteristics of EVCI. Oslo is classified as a large city with respect to 2020 population record, whereas Beijing is classified as a mega city. This may clarify the higher value for the number of public chargers per million population for city of Oslo compared to Beijing (Fig. 25). From Fig. 7, city of Oslo has shown a more mature level considering market categories of consumer; being in the late majority phase in 2019, whereas Beijing has shown less mature progress; being in the early adopters phase. Therefore, the key finding concerning city of Oslo's trend is that "*it managed with the minimum public charging infrastructure, having a minimum number of fast chargers, to accomplish a high service for EVs by maximizing the number of EVs/public charger*".

4.4.2. *Charging infrastructure surplus: The case of Amsterdam*

Table 5 shows that city of Amsterdam's EVCI incentives are towards both public and private charging, which may explain why it has a higher number of public chargers than Oslo (Fig. 25), as the latter's focus is towards private charging. The dominant EV type for both cities is BEV (Fig. 6), which indicates that they need the same characteristics of EVCI. Both Amsterdam and Oslo are classified as large cities with respect to 2020 population record. From Fig. 7, city of Amsterdam has shown a less mature level considering market categories of consumer in 2019; being

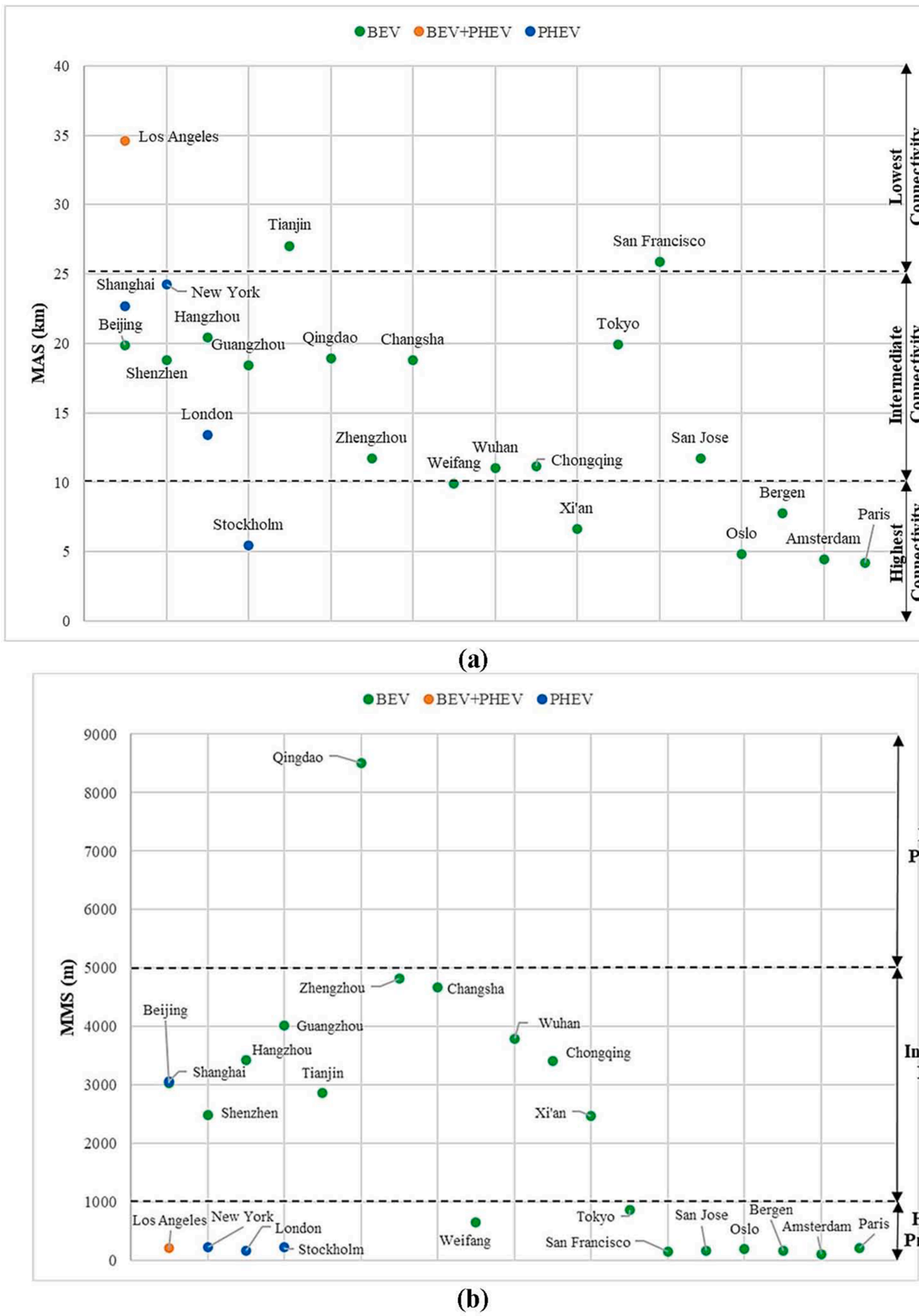


Fig. 23. Effect of Prevalent Degree of Electrification on the Service Radius of EVCI in Selected Mega EV Cities. a) Effect on MAS of Charging Pools, b) Effect on MMS of Charging Pools

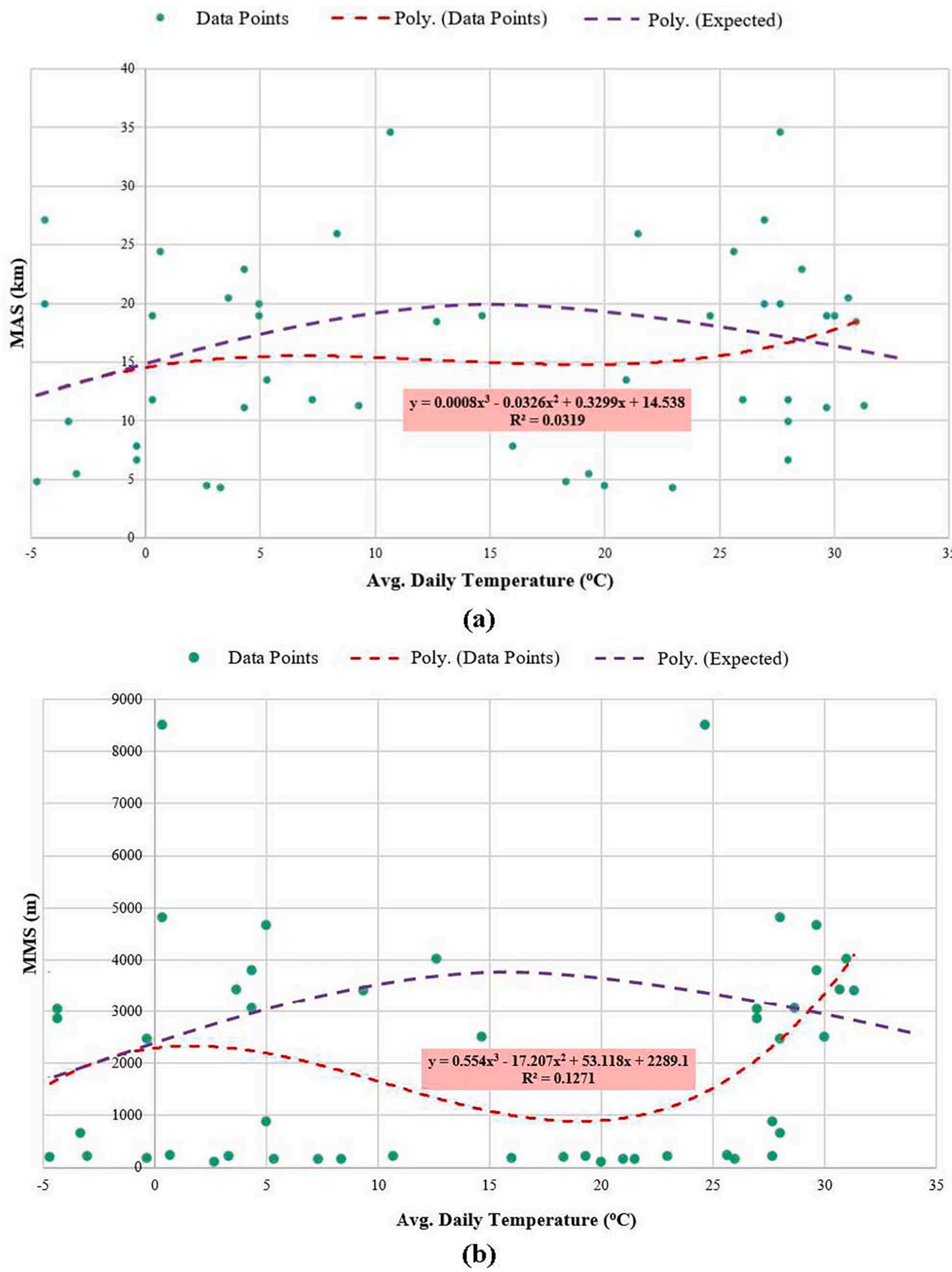


Fig. 24. Effect of Ambient Temperature on the Service Radius of EVCI in Selected Mega EV Cities. a) Effect on MAS of Charging Pools, b) Effect on MMS of Charging Pools.

in the early majority phase, whereas Oslo has shown more mature progress; being in the late majority phase. The key message in this comparison is that *"Amsterdam has over-invested in EVCI"*, as although it had a higher number of public chargers than Oslo, it reached a lower service of EVs (Oslo had 6 times higher value of EVs/public charger) and a lower value of fast public chargers per million population (Fig. 25).

4.4.3. Charging infrastructure operating concerns: The case of Shenzhen

Table 5 shows that Shenzhen's EVCI incentives are towards public charging, whereas city of Los Angeles' focus is towards both public and private charging. The dominant EV type for both cities is BEV (Fig. 6), which indicates that they need the same characteristics of EVCI. Both Shenzhen and Los Angeles are classified as mega cities with respect to 2020 population record. And with Shenzhen having the highest number of public chargers, this explains its higher ratio of public chargers per million population compared to Los Angeles (Fig. 25). From Fig. 7, Shenzhen has shown a more mature level considering market categories of consumer in 2019; being in the early majority phase, whereas Los Angeles has shown less mature progress; being in the early adopters phase. Though Shenzhen took the third rank with respect to cumulative sales of plug-in passenger electric vehicles from 2010 to 19 followed by Los Angeles (Fig. 6), and it had the highest number of public chargers with a higher number of fast chargers (Fig. 25), it achieved a very low service for EVs compared to Los Angeles (the value of EVs/public charger for the latter is approximately 9.5 times higher), although the latter was less mature considering the 2019 market categories of consumer (Fig. 7). This raises some questions about the operating efficiency of EVCI in Shenzhen and the robustness of the power grid system in this city, which affects the charging speed and thus the charging time.

It should be noted that there are other factors related to the EV model

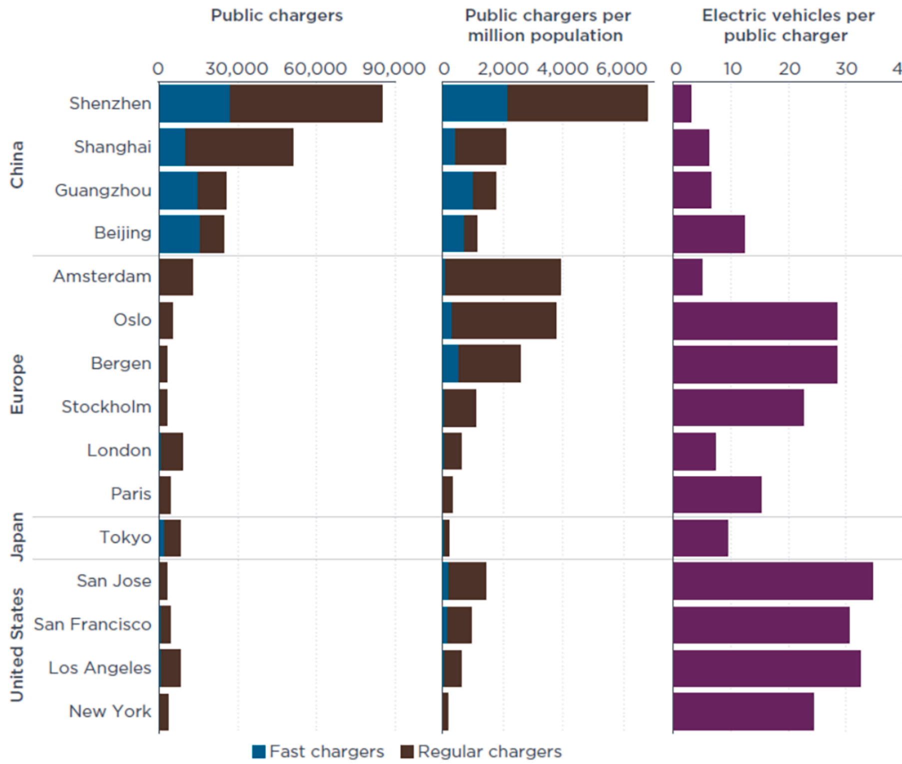


Fig. 25. Deployment of Public Charging Infrastructure in Selected EV Capitals through 2019 (Hall et al., 2020).

Table 5
Summary of EVCI Incentives in Mega EV Cities *adopted from* (Hall et al., 2020).

Country	Metropolitan Area	Public Charging Incentives	Private Charging Incentives
China	Shanghai	✓	
	Beijing	✓	
	Shenzhen	✓	
	Hangzhou	✓	✓
	Guangzhou	✓	
	Tianjin	✓	
	Qingdao	✓	
	Zhengzhou	✓	
	Changsha	✓	
	Liuzhou	✓	
	Weifang	✓	
	Wuhan	✓	
	Chongqing	✓	
	Xi'an	✓	
Japan	Tokyo	✓	✓
Norway	Oslo		✓
	Bergen		✓
France	Paris		✓
United Kingdom	London		✓
Netherlands	Amsterdam	✓	✓
Sweden	Stockholm	✓	✓
United States	Los Angeles	✓	✓
	San Francisco	✓	✓
	San Jose	✓	✓
	New York		✓

and the surrounding environment that may affect the charging time and thus the serviceability of a charger such as: battery capacity, temperature, and state of charge. For example, as the battery capacity increases, it will take more time to charge an EV and thus will decrease the number of EVs served by a specific charger (Hall et al., 2020). This may/not justify the low serviceability of EVs in some countries when comparing the number of EVs/public charger. However, limited by the data available, it cannot be confirmed in this research.

5. Conclusion and future works

This paper presents a data-driven multi-dimensional serviceability analysis of EVCI in 25 Mega EV cities by investigating: EVCI service coverage, service radius, and standard evaluation metrics in relation to: cities' characteristics, policies, and e-mobility market maturity. The provided analysis shall provide a guidance for cities at the early market stages of e-mobility to adopt the best practices of EVCI installation. Furthermore, it will spread these practices among e-mobility forerunners so as to further optimize future EVCI placement.

The key lessons learned from Mega EV cities can be summarized as follows:

- **EVCI hierarchy** across published data sources varies distinctly. Standardization of these structures or at least referencing methodologies to transfer from one hierarchy to the other among markets, would help in the accurate global evaluation of current conditions, exchanging practical lessons among countries, raising awareness, and saving time and effort.
- **Service area coverage** analysis in Mega EV cities has yielded three explicit perspectives: a) from a city-city viewpoint, cities had three levels of maturity (mostly-covered, medium-covered, and low-covered zones), b) from a market perspective, there was a reciprocal structure between compact and elongated patterns considering EVs sales versus EVCI coverage. The most elongated sales pattern was observed in the Chinese market and the most elongated infrastructure coverage pattern was observed in the European market, c) from a worldwide outlook, there were three patterns; accelerated infrastructure, accelerated sales, and mediocre patterns. A multi-dimensional model, relating average annual EVs sales as well as city-city and worldwide results, is then developed. This model can form a starting point for governments starting in a green field to plan for their EVCI.

- **Having a deeper look** at the **service area coverage**, there was a consensus that Mega EV cities locate at least 1 charging pool per 1 km^2 covered cell. The density distribution of EV charging pools in Mega EV cities has proved that EVCI is demand-driven with a scale-free network structure. There was a clear egalitarian pattern in the Chinese market and an aristocratic one in the European market. For the U.S. market, there was an intermediate trend. High-density zones of EV charging locations were proved to be related to city urban settlement pattern; where most nucleated cities had centered zones, all linear cities had linear zones, and all dispersed cities had scattered zones.
- **Service demographic coverage** analysis in Mega EV cities has shown a clear contribution to the type of parking citizens have access to in a city and drivers' charging preferences (ex: home charging, workplace charging… etc.). Local governments should consider having a database for private charging at homes and work facilities to help identify real gaps in EVCI and thus bridge these gaps with appropriate solutions (Hall & Lutsey, 2020b).
- **Service radius** analysis was constructed using two measures: a) measure of centrality (MAS), which is expected to be of due importance for highway trips, and b) measure of proximity (MMS), which is expected to be of due importance for city trips. Despite the fact that the spacings between charging pools were calculated as straight-line distances (not considering the geospatial road network layer), the effect of city road network topology has emerged in the results of the measure of centrality. The more centralized the road network topology (e.g., radial and circular) in a city, the more connectivity was observed between charging pools (i.e., less MAS values).
- **The prevalent degree of electrification** is anticipated to be of great importance, especially at early market stages of e-mobility. However, there wasn't an evidence showing that e-mobility forerunners have considered this factor while planning EVCI.
- Though **traffic conditions** is a micro factor affecting EV energy consumption, when projecting the trend of one of the previous research efforts on the service coverage and radius of EVCI, most of the results were rational having the coverage and spacings of EVCI increase/decrease respectively at free-flow conditions compared to congested conditions. However, the low R^2 value of the fitted models indicated weak models, if used for predicting the service coverage and radius based on TomTom congestion level. Such patterns and trends shall be continuously interpreted as TomTom index is just one high-level aggregated index that is meant to relatively rank cities rather than capturing the micro-level traffic congestion analysis.
- The **effect of ambient temperature** on EV energy consumption is concluded to be an asymmetrical U-shaped distribution, having the highest energy consumption at extreme hot/cold temperatures. However, the results of the service radius analysis didn't show the inverse U-shaped trend expected. Moreover, the low R^2 value of the fitted models indicated that these models are weak to be used for predicting the value of MAS or MMS based on the ambient temperature. It should be noted that this level of analysis was meant to uncover any clear pattern of association between the structured variables. It is no way an attempt to force a specific conclusion rather complete the exploratory intrinsic of the studied subject given its multi-dimensional nature and complex correlations.

Findings from this research have the following limitations:

- Data availability, especially for China Cities.
- Analysis grid size is 1 km^2 x 1 km^2, with no further categorization of accessible (populated) cells based on population density.
- When analyzing the advancement of Mega EV cities concerning the cumulative sales of plug-in passenger EVs (2010-19), this research didn't investigate if cities with lower sales of EVs, did have a high-utilized public transit system, thus explaining these low values.
- Average annual sales of EVs were computed by dividing the cumulative sales (2010-19) by its period, limited by data availability for the annual growth of EVs sales for each city.
- Analysis scope base, for example: When analyzing the effect of traffic conditions on the service radius of EVCI, TomTom Traffic Index represents a macro-level index for the whole city, while the measure of centrality (MAS) is a micro-level value.
- Cities of scope didn't have the characteristic of extremely hot temperatures like in Saudi Arabia, Qatar, and Kuwait, thus may be affecting the patterns deduced between MAS or MMS and ambient temperature.
- This paper didn't consider public acceptance of EVCI installation. Eventually, it is not just about developing planning tools for EVCI. Negotiations between citizens, local authorities, power-grid operators, and EVCI operators should be present. This shall form a decision support system for validating proposed scenarios and thus making any necessary modifications.

While this research attempted to answer a specific question addressing what are the key lessons learned from EVCI implementation in 25 Mega EV cities; it triggered even more interesting questions. Below are key future research directions that can emerge from this research:

- The multi-dimensional serviceability analysis of EVCI can be further upgraded by:
  a) Incorporating Google Maps Geocoding API in developing a harmonized robust database for EVCI locations.
  b) Introducing other city characteristics (i.e., transferability elements), such as:
     1. Public transit rollout in a city.
     2. The motorization rate and passenger-km ratio
     3. Trip characteristics (e.g., origin, destination, etc.)
     4. Trip maker characteristics (e.g., gender, income, age, car ownership, technology familiarity, etc.)
     5. Charging levels of existing EVCI
  c) A comparative study for calculating EVCI coverage using different methods, highlighting the advantages and disadvantages of each approach. New methods can include estimating a weighted average for covered cells based on: population density, daily traffic volume, or travel time.
  d) Using Google Maps platform to calculate road-based distances for EVCI service radius measures.
  e) A comparative study for calculating EVCI service radius measures using different methods, highlighting the advantages and disadvantages of each approach. New methods can include estimating a weighted average for cities based on city size while calculating the measure of centrality.
  f) Further investigation of the effect of traffic conditions on the optimal siting and sizing of EVCI, where other sources/indexes for evaluating traffic conditions can be used like: Google Maps platform.
  g) Further investigation of the effect of ambient temperature on the optimal siting and sizing of EVCI.
  h) Modeling the effect of driving behavior, city topography, and different speed profiles on EV battery range and thus on the optimal siting and sizing of EVCI.
- Developing a layered decision support system framework to validate proposed scenarios of EVCI placement.
- Feasibility studies for vehicle-to-grid (V2G) technology in relation to promoting home charging and the service efficiency of EVCI.
- Modeling net emissions and air quality comparison between private cars electrification vs zero-emission-buses, and shared mobility applications.

Declaration of Competing Interest

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

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