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Spatial Modelling for Determining Electric Vehicle Charging Station Allocation in North Jakarta

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Abstract- The rapid gradual shifting of electric vehicles (EVs) as a part of the green transition of electric mobility (e-mobility) has brought one of the most challenging issues for the urban planner on how to allocate the Public Electrical Vehicle Charging Station (PEVCS) for future urban ecosystems in a technical and economic viability achievement. This study employed the Neural Network method, which uses a supervised learning model to simulate a model with two essential parameters: the Origin to Destination (OD), which is modularly arranged over a square area of 5×5 kilometers per square, and the energy consumption prediction. The number of EV units is limited to twenty-five thousand for computation efficiency, and the study area is located in North Jakarta, Indonesia. Markov Chain Model (MCM) and Monte Carlo Simulation (MCS) were applied in the simulation. The electric power grid as a supply point of connection (PoC) was included in the computation. The proposed model aims to bridge the gap between the demand requirements of PEVCS based on the commuting behavior of EV users and the charging point on the availability of existing supportive grid infrastructure toward urban landscapes and innate traffic nature, especially in the initial transitioning of developing countries which are different compare with Europe, China, and the United States. On the basis of the model traffic density, battery consumption, proximity distance between the supporting grid feeder, and on-the-go user behavior, it is recommended that the PEVCS is suitably allocated in the commercial area 66.6 % out of 33.3 % for residential areas.

Keywords Electric Vehicles, Public Electrical Vehicle Charging Station, Neural Network, Electric Infrastructure, Randomization Component, Point of Connection

1. Introduction

The public electric vehicle charging station (PEVCS) is the essential infrastructure for electric vehicles, and how to govern the optimal allocation has become a challenging issue in all countries. Consequently, the charging station placement can be very unalike depending on government policies, network availability, and local communities. Generally speaking, the Asian markets for EVs in Indonesia do not fundamentally refer to the intention of reducing carbon emissions only but also avoiding government regulations restricting commuters from driving on the main street and tax deductions. Therefore, most EV users also have a conventional car as the first option. The assessment of why EVs are only popular as a second option for commuting transportation can be further read in another publication [1]. In line with this, EV distribution is mostly denser in the urban area, making its services less available in rural areas, and EV users in Indonesia are afraid of using EVs for long, traveling across to other regions from central cities. However, this study attempts to assess the feasible location for a PEVCS to support the development of EV networks in the suburban area in North Jakarta. The case study is taken on North Jakarta, which is prominent as a port area, and the traffic of people and goods is intensive, which makes it suitable for future evident based-research. Although conventional automobiles still occupy a considerable portion of private and commercial vehicles in Indonesia, a glimpse of market change from emission vehicles to e-mobility vehicles has happened and will continue growing in the upcoming days. When it comes to emissions, traditional engines contribute to the release of greenhouse gases (GHG), EVs can positively lower the effect of CO_2 (carbon dioxide), CH_2 (methane), and N_2O (nitrous oxide) in the atmosphere through specific periods [2]. If we look in detail, there are two categories of EVs based on their drive train systems: battery EVs (BEVs), which rely entirely on an electrified powertrain system powered by the battery system. The power is kept in a battery system and released when required by the so-called battery management system (BMS). More efficient motors in the drive system extend the driving range and decrease battery size requirements. While hybrid EVs, whether plug-in or pure hybrid, use a conventionally fueled engine combined with a battery system. A pure hybrid uses a fueled engine as primary and simultaneously generates restored power through regenerative braking and reuses it when needed without any direct charging connection to the power plug. Whilst plug-in uses the combustion engine for the secondary to repowered the main electrified drivetrain powered by a battery system. Similarly, BEVs and plug-in hybrid EVs (PHEVs) must be charged from the power grid: through charging on-grid or off-grid mechanism. Aside from that, the power rating charger is categorized into three charging levels: low, fast, and ultrafast [3].

In this study, we exclude individual home charging, unlike in the previous research [4], which uses it as an option. We realize that not all commuters will install additional electric power in their house which will be actually raise their utility bill. Since majority of households in Indonesia have an electric power range from 1300-3300 kVA for their electricity power[5]. So, charging an EV in own private house would be bring an extra cost and possibly take a long time to fully charged (slow charging level). In addition, the safety and environmental issues in a developing country like Indonesia are also considered; a similar study about how criminality and environmental problems (flooding and land subsidence) indeed can affect the allocation of PEVCS in developing countries. This issue can be further read in other publications [5]. Another rethinking is that the growth of the EV industry is influenced by where the government is siding [6]. Thus, this study attempted to determine how significant the placement of the charging station is based on geolocation and spatio-temporal modeling leveraging remote sensing techniques (travel orientation, proximity distance, and routes delineation) and artificial intelligence (Neural Network, Markov Chain, and Monte Carlo Simulation and Traveling Salesman Problem) as supporting methods [7], [8]. While the majority of scientists have thoughts about EVs and their relationship to the socioeconomic condition and grid feeder stability found in [9], those rarely take a point of view from electrical infrastructure accessibility. Open spaces and parking lots might be prospective places for an allocation of PEVCS in developed countries or sustainable municipal areas, as this is also supported by previous research[7], [9]. Nevertheless, this is not always relevant for developing country to where open space and parking are not continuously prevail.

In the context of environmental conditions and EV types [11], some EVs that can be detailed through useful references found in ev-database.org or factory release [10] have different battery capacities and modes of driving features. Hence, our simulation unavoidably tackles divergences concerning those parameters. Another consideration arises since third-world countries mostly do not have strict regulations and firm planning for household power electricity yet; thus, consumers can inquire for additional capacity by renewing the existing subscribing contract through the utility to establish home charging units (HCUs) [11]. In line with that, Indonesia's climate and atmospheric conditions can vary over the time hours; heavy rainfall and heat temperatures can suddenly occur multiple times uncertainty and may degrade EV batteries. Hence, it potentially reduces battery capacity and useable lifetime cycle. Moreover, frequent air conditioning is mostly used to cool the cabin temperature and provide convenient air due to heat and air pollution in Jakarta [12]. The spatial planning for PEVCS optimization based on the supply and demand in a certain area was demonstrated by He et al. [13] in their publication. They stated that the "presents data may not inherently resemble the future demand of EV charging facilities" and revealed that having different charger types in one PEVCS rather than creating the new one is better.

2. Literature Review

a. Conceptual framework

Spatio-temporal implementation for identifying the best allocation for PEVCS has been used in some literature; one of the comprehensive methods is what had done by Yi et al. [14] in their publication. They deliver information about statistical analysis and behavior analysis, concluding that charging station is better to install in working area than in residential area as a second list. Through prior studies, the analysis to determine the optimal location for charging station placement had been performed by employing Monte Carlo Simulation to generate randomness variables and presenting scientific modeling; this deliver satisfactory results if incorporated with the hidden Markov chain model as the conceptual framework to illustrate the cycle of movement in time series [15]. The EV itself needs to be considered when implementing the spatio-temporal EV charging station is the EV itself, and previous research declares that they cannot use the real object in real condition if the large number of EVs is part of their model. Hence, agent-based modeling (ABM) is being introduced as a solution [16]. Through it, the data driven for EV mobility to determine PEVCS can be simulated, and how they are connected with surrounding parameters like travel routes, travel distances, energy prediction, and socio-economy conditions can be attached, as this is similar to what is performed by actual monitoring model with realistic data. The difference might be only for detail of EV registration number and traffic frequency [17]. Meanwhile, the Geographic Information System (GIS) is great knowledge to help understand better the distribution of the model and figure out the character of charging stations and type based on community needs and supporting infrastructure, i.e., grid-feeder and load capacity constraint. Hence, they have become vital in scientific analysis and interpretation. Moreover, the combination of GIS and righteous decision-making methods can result in efficiency in engineering and economic problem for PEVCS, as mentioned in [5], [18].

According to Presidential Regulation Number 55 of 2019, electric vehicles will be used to substitute the number of combustion vehicles. The regulation reflects the desire to improve the climate for the production and operation of electric cars in Indonesia as well as plans to limit the use of fossil fuels for motorized vehicles. The regulation also covers the legal aspects of charging stations: public charging stations (gas stations, government offices, shopping centers, and public parking lots) and private charging stations (government offices and residential areas). In addition, in the framework of accelerating the implementation of the electric vehicle program, the President of the Republic of Indonesia issued Instruction No. 7 of 2022. The presidential instruction regarding using battery-based electric motorized vehicles (Battery Electric Vehicles) as operational service vehicles and/or individual vehicles for central government agencies and local governments The electric motorized vehicle acceleration program must be balanced with a proportional distribution of charging stations. On that occasion, spatial modeling was used as part of our analysis, a fascinating tool that enabled us to determine the best EV charging station placement. In fact, as the intricacy of the situation increase, the model can be evolved. This model's approach utilized neural network techniques. Similar to prior research [19], [20] performed a machine learning (ML) combination and the Monte-Carlo method to gain spatial sensing and weighted-nearest point values in the geo-model. This study develops and fills the gap between scientific and communal needs to determine the best EV charging station allocation in North Jakarta, Indonesia.

Conversely, our model does not explain electricity needs in every sector in Indonesia and the detrimental effect of an EV charging station on the grid; therefore, further reading can be read in other relevant publications [21]–[23]. Other interesting research about how to manage the power control system for EVs that take sources from renewable energy to decrease energy consumption from the standalone electrical network can be detailed in some publications [24], [25]. Since we tend to approach the allocation of PEVCS based on the user pattern side and strive out the load penetration and any further effect that influences the grid ecosystem, we recommend comprehensively reviewing another publication that focuses on this matter [26]–[28]. Generating the network model of EV by route tracking to estimate the best location of charging stations can be accomplished by employing the GIS technique and some R-code for DL implementation. The R-code is widely known for GIS integration and has a robust library like phyton, an open-source programming language [29].

b. Public EV Charging Station model and its assignment

North Jakarta, one of four prestigious urban residential areas in Jakarta, may be fostered as a modular area to simulate EV charging installation. When taking part in the network ecosystem and grid interaction, PEVCS can have a critical impact on the user in an urban area; these groups of users have different backgrounds, such as educated individuals, high-income personnel, or young to mid ages persons [30]. This also put a mindset for the majority of Indonesian people that EVs are still categorized as expensive vehicles; hence, ownership is mostly from full job person with mid-high income individual with an awareness of technology understanding and has more than one vehicle, which conventional car should be in place among [1], [31]. Accordingly, due to low-income user can afford to buy EVs out of the region where they are settled and can be excluded from our proposed modular model. To generate a model based on those criteria, we attempt to look over the socio-economy level, which is also similar to previous research about the extent to which the individual buys EVs in uncertainty regulation [32], [33]. The detail of the area of interest (AoI) can be seen in Figure 1. The ArcMap software and R-codes are used in the simulation model. In correlation with that, three models of automobile specification were selected as part of this study; this is a common EV model in Indonesia. Therefore, we have to make a case and assumption in this model to limitate the computational process and deliver relevant information to the prospective readers. We generated an arrangement of steps and assumptions which can facilitate the model:

Step-1: identification of prospective place

Premise 1: EV vehicles are relatively expensive in third-world countries; thus, mid-high-income individuals is preferable consumer for market sale [34], [35].

Premise 2: The urban city is well developed than suburban or even rural areas; this also become the main concern of EV consumers to stay and live in the urban area [14], [36]

Step-2: Characterized EV types

Premise 1: the low-mid ranges EV is a favourite in the urban area. Also, hybrid types of vehicles are still relevant to whomever citizens want to travel across the city supporting neighbours, although the number of them is still in small proportion compared to the overall EV user; this explains the "range anxiety" of EV users when traveling out of the city [37].

Premise 2: BEV is the basic model in this simulation, which is relevant to the three types of vehicles being modeled in this study. No hybrid types or another green powered vehicle, i.e., fuel cell and related gas powered vehicle [23], [38]

Step-3: Infrastructure readiness

Premise-1: the closer PEVCS with the grid utility, the lower cost of the infrastructure that needs to be built, and some recommendations to change charging time to daytime charging to shift peak load to the nighttime are also preferred as found in [37], [39].

Premise-2: Grid connectivity and IoT (Internet of Things) can be crucial to EV users to monitor the traffic charging during peak load and scheduling or rerouting their vehicle to the quieter charging station [40].

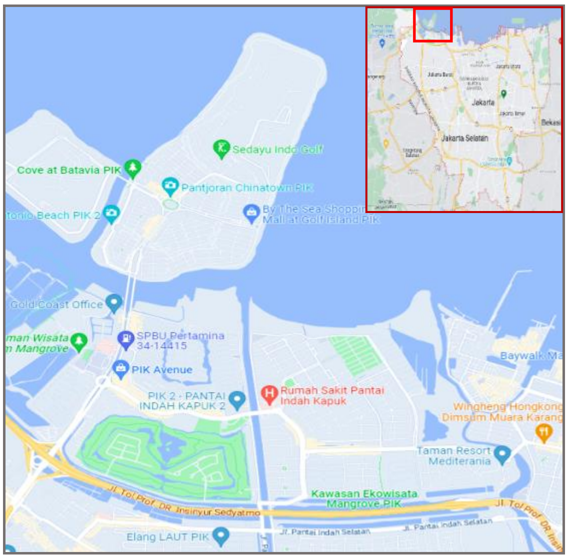


Figure 1. The simulation area of the EV charging station based on network analysis in GIS.

Step 4: Travel distance and trajectory

Premise-1: the mobility of EVs is limited to this modular region with no transfer from outside and no leaving vehicle from this study area

Premise-2: the distance is not limited; however, the time for the model is only twenty-four hours of observation with five stops; the location of stops can be varies based on the programmable random variables (PRV) [41]. The stochastic model was developed when applicable in this simulation model.

To accomplish our study, we generated the route's network based on the road position in the study area, and the vehicle track can be determined based on this road network (see figure 2)

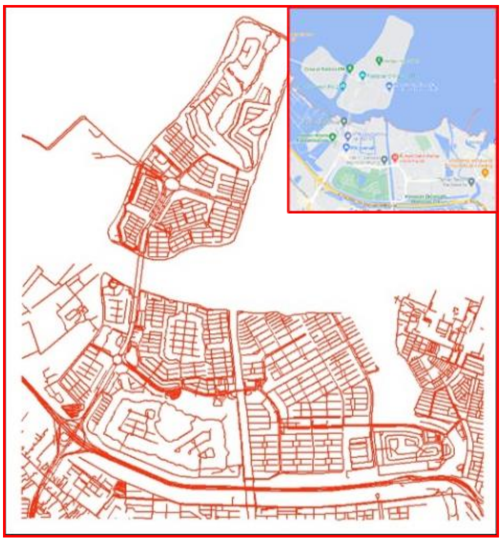


Figure 2. Roads map in the study area

In this simulation, three types of EV brands take into the model; (1) Tesla Model S, (2) Hyundai Ioniq 5, and (3) Wuling EV. The attainable distances were then evaluated based on the factory statement, and we realized that those depending on every user's driving styleit might be less or more than what it stated in factory manuals[42]–[44]. For PEVCS types and conditions, we refer to what stated by Mastoi et al. for the requirement of public charging and semi-fast charging [45]. Those can be seen in Table 1

Table 1. Electric Vehicle Charging Infrastructure (Modified from [45])

Type1	Type2	Type3
		
Home charging	Work and Public Place Charging	Dedicated placed charging
EVs are charged via AC power supply at normal (level-1)	EVs are charged via AC power supply at semi-fast (level-2)	Electric Vehicles are charged via a DC power supply at a fast (Level-3)
Voltage 120V 1-Phase AC, charging Loads 1.4-2.5 kW	Voltage 208 V or 240 V with 1-phase AC, charging Loads have a range between 2.5 to 19.5 kW	Voltage 240V or 480 V 3-phase AC, charging loads have a range between 45-90 kW

Following on what is in table 1, PEVCS is recommended in accessible space, away from flood and routinely passed by EV either in day or night. The Tesla Model S specifications can be looked into in detail on their company pages [43], similar to Hyundai Ioniq 5 [44] and Wuling EV [42]. Before completing the input for the simulation model, we set up the EV driving behavior by random values generated from user experiences in conventional automobile. Therefore, some fluctuations in state of EV while traveling during a day trip approximately can be seen below. The illustration can be seen in Figure 3.

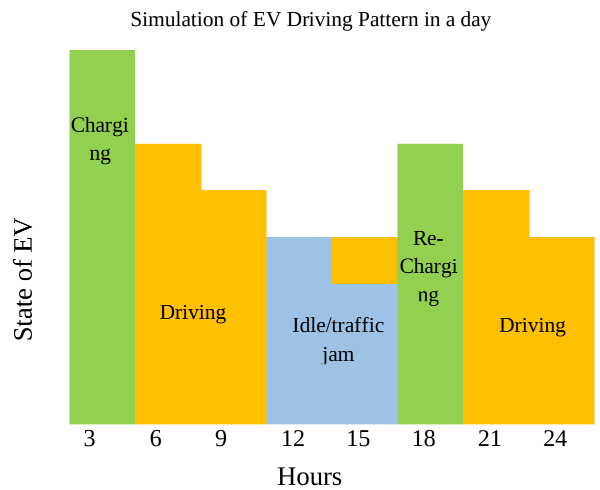
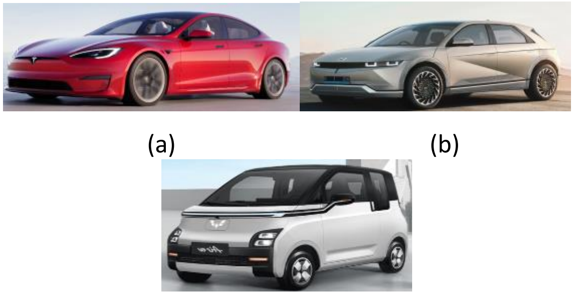


Figure 3. Illustration of EV driving pattern

This study took samples of three small EV cars which can be seen in Figure 4 (real images can be different depending on the user's own).



(a) (b)

(c)

Figure 4. The design of EV vehicles in this study Tesla Model S (a), Hyundai Ioniq (5), and Wuling EV(c).

3. Implementation of Spatial Modeling

The spatial relationship between the energy infrastructure and trip distance from EVs is examined in this study using spatial modeling. As a result, they can be employed to establish the best placement for the electric vehicle charging station. Shapefile data from OpenStreetMap and the Environmental Systems Research Institute (ESRI) database were used in this simulation. Furthermore, Figure 5 depicts the study's framework.

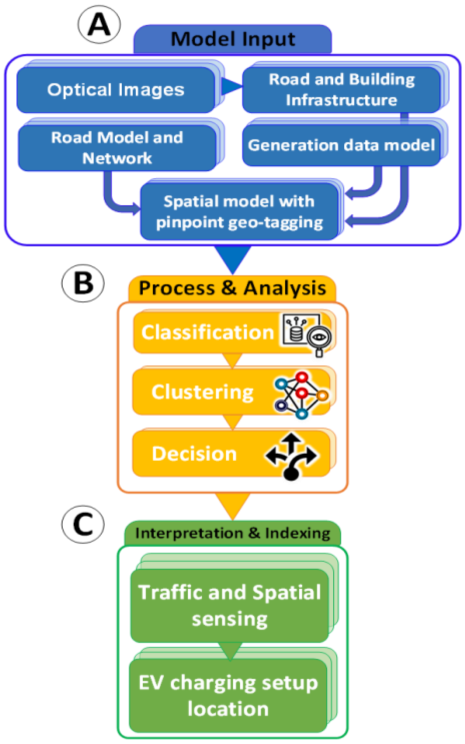


Figure 5. The simple framework concept of this study

Therefore, the R-code plays a prominent role in this simulation model, and a library pack is required to run the simulation. Further reading about how to create and synchronize the dataset to be able to be executed and plotted in R-Studio or, in another way, can be read in Lovelace's publication [8]. Geocomputation in R-codes is something powerful and user-friendly. Lovelace et al.[8] in their publication, explains the application of geocomputation in R-codes for transportation models, employing the "sf", "terra", "spData" and "OSM" packages for demonstrating the transportation model from a zone of origin and zone of the destination.

The complex transport modellers using geographic analysis enable to capture of the transport system's substantial meaning and network, demonstrating the potential spatial sensing analysis [46]. The approach method of traffic network originated from the theory of the travelling salesman problem where are selected the shortest routes through a group of N vertices (*N* is a number of network's nodes) [47], [48]. We attempt to perform the same steps by dictating the EV vehicle's stop, not only two nodes (start and end of the trip) but five nodes in series (start, three temporal stops, and end of trips), this called as Origin to Destination (OD), as seen in Figure 6.

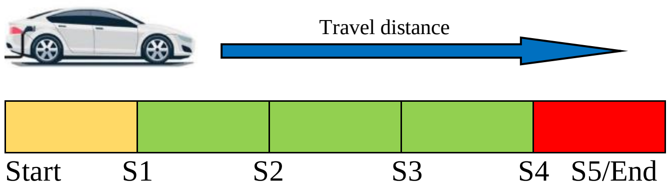


Figure 6. The traveling scenario to simulate PEVCS in an urban area (modified from [45])

Where S is the stop point, according to the design of the logical trip, If we had 2500 EV cars, then 12500 nodes could be generated. Those nodes represent the movement of a vehicle in time series. The travel distance of the simulated vehicle can be seen in figure 7. However, what is in figure 7 is just a few samples because plotting all vehicles will reduce the clarity of the spatial distribution map and is not representable for this article. Furthermore, The start and stop point of the EV is still in the AOI (no vehicle trip outside of the boundary area).

Figure 7. The spatial distribution map of the EV sample inside the AOI with five stops point (different color means different vehicle ID)

Following the previous input dataset, the EV specification has been included in the model, and we are attempting to search for CCTV records in the nearby zone. However, no record can be accessed freely, so the artificial data was made in the sense of traffic density and logical concepts. If the velocity of the EV is related to the duration of the trip, the empirical equation can be written as:

$$v_t = \frac{(x_e - x_i)}{t_{ei}}, \begin{cases} e \geq 0, e \text{ is integers} \\ 0 \leq i < e \end{cases} \tag{1}$$

Where the v_t is the velocity of EV, e is the end position (in kilometers), t_{ei} is the duration of the trips in seconds, x is the distance of the trips, and i is the initial/start position. A detail of the frequent stop-and-go model is illustrated in Figure 6; additionally, the speed prediction with adequate traffic flow model and neural network decision making can be read Li et al. [49] publication. In simple way, the empirical equation to estimate the trips-track distance can be written as [50]:

$$\int_{i=0}^{e} v_t \partial t = \sum_{i=0}^{e} \int v_i \partial t + \int v_{i+1} \partial t + .. + \int v_{i+..+n} \partial t \tag{2}$$

Since the dragging force c, and h is driving behavior can be a factor that affects the velocity of the EV, F is the force factor, q is forward forces from EV's torque, N is the perpendicular normal force, b is pulled force from brakes when activated, and d is road surface roughness, then the equation for an estimate the travel distances can be simplified into:

$$c = \sqrt{{F_q}^2 + {F_N}^2 + {F_b}^2} + d \tag{3}$$

$$h = \sum \frac{S_P \pm v_r}{t_{ei}} \tag{4}$$

$$\int_{i=0}^{e} v_t = \sum_{i=0}^{e} \begin{matrix} (c_i + h_i + \int v_i \partial t) + \cdots + \\ (c_n + h_n + \int v_{i+..+n} \partial t) \end{matrix} \tag{5}$$

Where S_P s pressure to the pedal and the remains velocity, it can be 0 if the vehicle starts from the beginning. the traveling salesman problem (TSP) concept can be related to the EV trips in our AOI and simulation model.

The TSP and MCM are essential to selected the fastest route in the traffic network in AOI. Recent research about how it was able to help to solve the PEVCS allocation model issue through some alternatives can be seen in table 2.

Tabel 2. information summary of the latest research on PEVCS allocation modeling based on spatial planning.

Researcher	GIS	MCM and/or MCS	TSP	ABM	Neural network or other decision making method
Rodrigues et al., 2019	√	√			
He et al., 2022	√				
Xu et al., 2023	√	√			
Wu et al., 2023	√				√
Pillai et al., 2022	√			√	
Costa et al., 2018	√				√
Shepero & Munkhammar, 2018	√	√			
Li et al., 2022	√				√
Yi et al., 2020	√				√
Anand et al., 2020	√	√			
Gauglitz et al., 2020	√				√
Huang et al., 2022	√			√	
Li et al., 2023	√				√
Jenkins & Kockar, 2022	√	√			√
Ge et al., 2020	√	√			√
Tikka et al., 2022	√				√
Zhang et al, 2022	√				√
Pagany et al., 2019	√				
Li & Jenn, 2022	√				√

According to the summary in table 2, the spatial modeling have been used by all of the previous researchers. Therefore our study uses the same way for GIS as the basis for analysis, ABM for real-time approaches, MCM for the stochastic model, MCS for randomness OD, and add in the TSP as the algorithmic employed by EV user to select the fastest routes (driving behavior), which never being used by any prior researcher above, this expected to bridge the gap from what they did before. Intending to give worthy recommendations, we calculate the proximity of the nearest electricity tower to a potential feeder (which can be immediately installed) to generate possible PEVCS.

On the other hand, the charging station infrastructure connected to the grid has several types of locations, whether commercial, workplace or residential. Figure 8 shows the power supply distribution from the utility grid to the consumer location in different voltage and dedicated locations [15]. This topology strongly relates to the decision to allocate the public charging station.

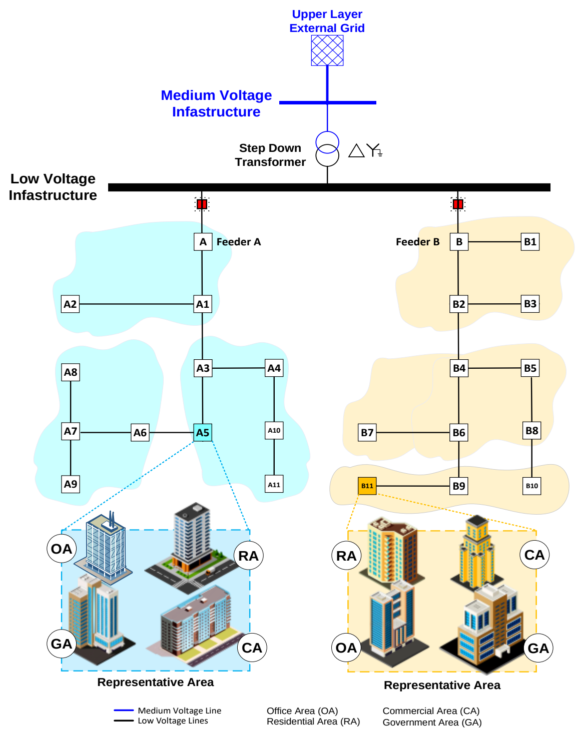
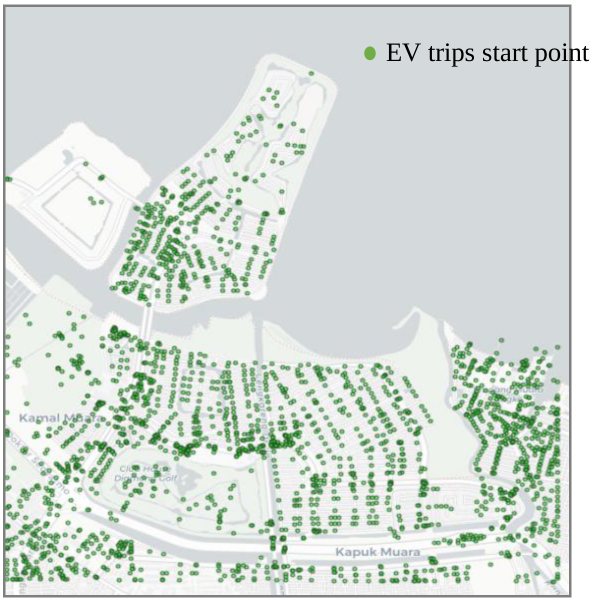


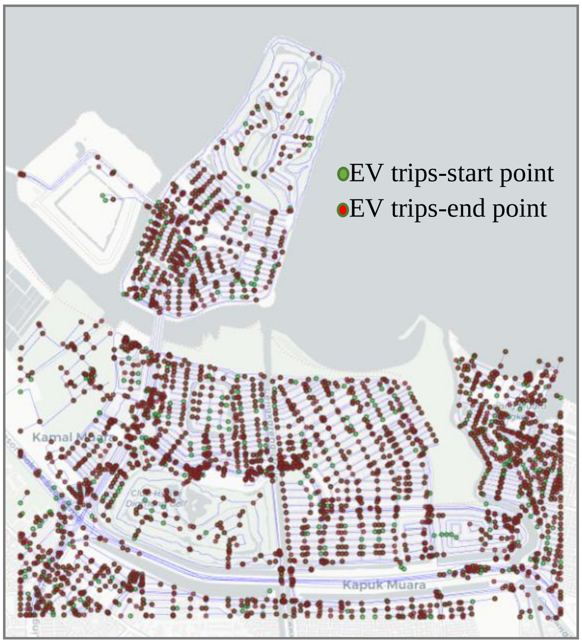
Figure 8. the illustration of power supply distribution with voltage infrastructure variation to support an allocation of PEVCS demand (modified from [15].)

4. Network Modeling and Analysis

Because we had time series movement of the EV, we can calculate the reachable distance from the EV by network analysis in GIS (by conduct sophisticate samples) and perform the TSP to estimate the rest of the simulation (see Figure 9).



(a)



(b)

Figure 9. The simulation of EV travel distance with start (a) and end point (b) in the AOI (the travel trajectory samples is previously shown in Figure 7).

From our model, the TSP takes the main part of the process after OD has been declared; the analysis regarding the best route for trips inside the AOI was accomplished by R programming language with "terra", "spData", "sf" and "tmap". Where it driven to an analysis of how much time spent during the travel process. This destination route can be plotted and seen in Figure 10.

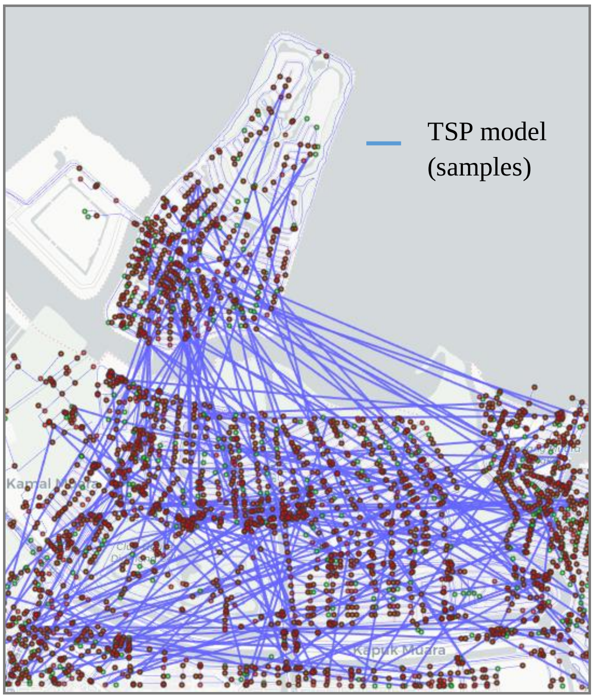


Figure 10. TSP model in AOI, based on the five traveling scenarios for EV, this is important for determine the frequent stops area and potential PEVCS.

Since the problem of driving behavior is more complex than just declared "stop and go", as explained in equation (4), to where the situation is close to the non-linear approach. Furthermore, the random simulation of driving behavior can also be conducted by generating the EV's pedal intervention aside from TSP algorithms, as illustrated in Figure 11(a).

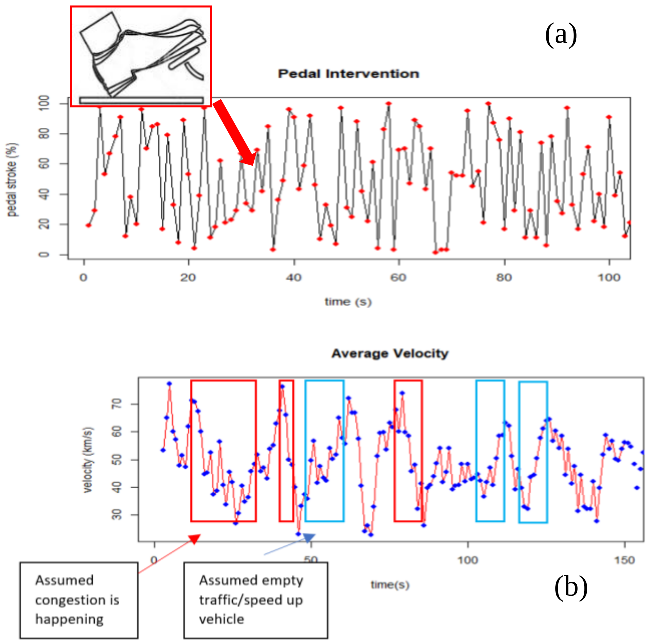


Figure 11. (a) An illustration of pedal intervention (b) and the velocity samples changes of EV during the trips that affect the driving behavior.

Moreover, since we have generated the velocity value from twenty-five hundred EVs in AOI, each EV can give an outcome of velocity and distance in time series; the variation of the EV's velocity can be seen in Figure 12.

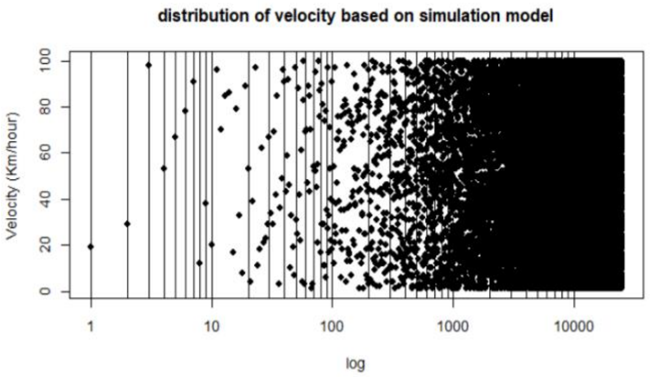


Figure 12. The scatter graph of velocity distribution based on the simulation model, which is generated by the velocity changes of EV during its trips (a)

In our study, we estimate the reachable distance in one hour; this is necessary because we can predict the distance in one hour and estimate where the EV will drainaged its battery (if there is no charging in the travel simulation). So, the illustration of attainable distance based on the EV simulation model can be seen in Figure 13. Where in average, for one-hour trips, it's ±18.2 km based on the random generation of average velocity.

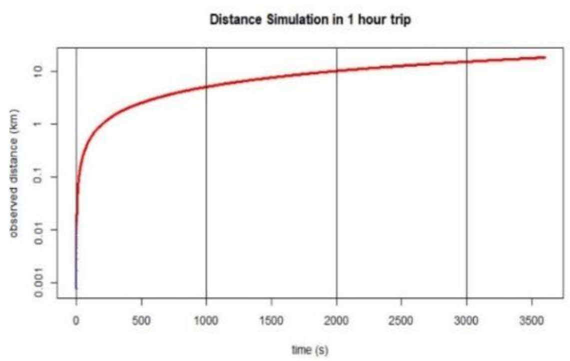


Figure 13. The simulation of distance based on EV trips in 1-hour observation.

However, we understand that our velocity model was likely to have less accurate than real data. So, to validate the result, we did several observations of the actual condition based on google street view and the nearest CCTV that directly through in and out to the AOI. We have taken the vehicle traffic in the AOI and associated it with EV. Figure 14 illustrates that premise.

The neural network model is implemented in this study simulation to determine the dense area often passed by EVs. That area should be considered prospective for EV charging station installation. To do that, we cluster the EV parameter such as velocity, relative position in the AOI, and trip distance and estimate the power consumption of the EV base on the manufacturer database and general data center for EV [10].

Figure 14. Sample traffic of the small part of AOI and surrounding conditions for urban planning of PEVCS.

Since traveling at AOI and Jakarta in general, when the daytime will increase the heat of EV, particularly inside the cabin, the EV user mostly turn on the air conditioning for cooling; this also consumes energy and drain the battery; therefore, we took temperature increment as our analysis part in a neural network. The neural network diagram can be seen in Figure 15. Later, the distribution map can be defined from the Figure 15 neural network data. This step leads to the denser region can be illustrated.

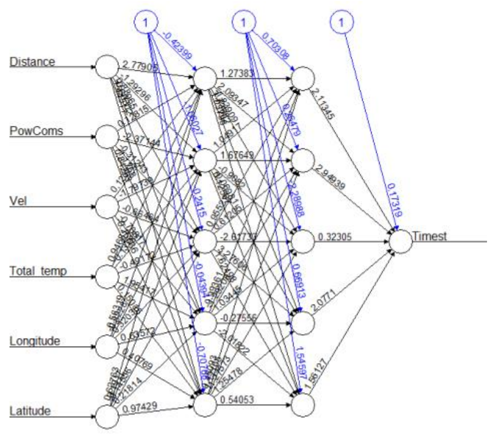


Figure 15. Neural Network diagram to estimate the denser region and useful to delineate the prospective region for PEVCS.

We are not using ROC (Receiver Operating Curve) to test the performance of a classification model because of the requirement to perform it; we must have the actual data of the EV, and that is not possible yet, due to there being no registered EV car in that large amount of number reside on the AOI, this study is to help future planning in EV if its become main transportation for the community in our study area.

The distribution map of EV traffic based on the MCS and TSP was then incorporated with artificial neural network (ANN) as decision-making (see Figure 16), showing some potential spots. The red color means that the area is frequently passed by EVs but does not indicate that the environment and infrastructure support it.

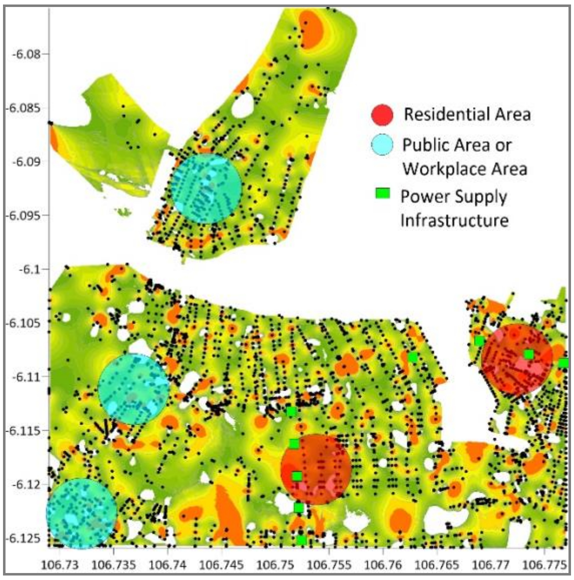


Figure 16. Result in Maps from the modeling simulation in the AOI

the following criterion corresponds to infrastructure; this component can be defined in table 3 below

Table 3. Component requirements for PEVCS in AOI

Description	Item
Public area (open space/parking lot)	√
Close to the Utility Power Supply	√
Less criminality and vandalism	√
Not in the flooding area	√
technology awareness (young till mid ages person)	optional

As a result of only five prospective areas (marked by circle-buffer in figure 16) for PEVCS, two of them are close to the infrastructure and allocated in a residential area with constant EV traffic, and three of them are close to the communal area like (market or workplace area), from this, we conclude that sixthy percent $\left(\frac{3}{5}\right)$ of PEVCS recommended built and install in the commercial area and fourthy percent $\left(\frac{2}{5}\right)$ in the residential area.

5. Conclusion

We did analysis for the suitable location for EV charging, the approach in driving behavior and spatial modeling was performed in this study. Furthermore, the network analysis in GIS was incorporated with MCS and neural network, and previous researcher has performed MCM; nevertheless, they did not implement the TSP algorithm. In addition, the TSP algorithm has been a powerful tool to generate the fastest route in the traffic ecosystem and estimate the EV trips in the simulation model. this study aims to bridge that gaps and strengthen the simulation model on top of that it helping communities in the AOI, to plans their needs of public charging installation. This study uses R-code as the main programmable language. The basic requirement for the EV charging allocation relies on five factors explained in table 3, but more importantly, the EV is still small compared to the conventional cars in this study area. Three brands were selected for our model (Tesla, Hyundai, and Wuling); they are simulated with ABM. Though the CCTV of AOI was not obtained exactly in this AOI, we validated our result with vehicle traffic from the closest CCTV near the AOI and used google street view to predict the mobility and assume the conventional as EV. We also take the complete specification of EVs from their manufacturer's web page. This study uses the geolocation and spatial concept with the attainable distance for brevity's sake and aims for the best place to install PEVCS in the area. Considering the security and infrastructure factors, it is revealed that a communal area with frequent EV traffic is preferable to dedicate as a prospective area for PEVCS. Even though the artificial dataset constructs the driving pattern based on the premise of congestion level, it's only a simulation that can deviate from the actual situation; it can be better or even worse in third-world countries. Based on the simulation, the EV charging station can be installed in a residential area and commercial area of AOI where the users stop/park their EVs, sixty and forty percent, respectively. The model in this study is expected to give new perspectives on how important spatial models are to EV business.

6. Discussions

EV is something promising today. A lot of market demand affects the production of automobile units, and this is a challenging situation when the supported infrastructure could be more optimum in developing countries, PEVCS is the main concern. Urban communities have become aware of air pollution and expect better transportation in their daily lives, EV is unavoidable to attract urban communities. Even though the price is still categorized as an expensive for some people, the hype still goes up. However, in this study, we observed the readiness of North Jakarta with AOI as the main object, which might be transformed into a smart city. Despite of what we did in this study, we have limitation particularly in data collection and filtering, due to no actual PEVCS in AOI location, we cannot justify which type of suitable public charging in North Jakarta.

Further research can study the social and economic impact of EV charging stations, whether it can increase the number of EV users or it will become costly in maintenance. The driving pattern and infrastructure have a significant role in EV development. Thus, stakeholders should make incentives and favourable regulations to satisfy EV users. The discussion about charging placement can be quite long if the social and economic factors included, the permission of the landlord and investors can influence them even more than the engineering recommendation. We remark that social science and appropriate regulation can help many city developments, including the EV industries in urban areas.

7. Nomenclature

PoC	Point of Connection
PEVCS	Public Electrical Vehicle Charging Station
MCM	Markov Chain Model
MCS	Monte Carlo Simulation
OD	Origin to Destination
TSP	Traveling Salesman Problem
IoT	Internet of Things
PRV	Programmable Randomness Variables
AOI	Area of Interest
ABM	Agent Based Model
GIS	Geographical Information System
ANN	Artificial Neural Network
ROC	Receiver Operating Characteristic Curve
CCTV	Cloased Circuit Television

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