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Initial location selection of electric vehicles charging infrastructure in urban city through clustering algorithm

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ABSTRACT

Transportation is one of the critical sectors worldwide, mainly based on fossil fuels, especially internal combustion engines. In a developing country, heightened dependence on fossil fuels affected energy sustainability issues, greenhouse gas emissions, and increasing state budget allocation towards fuel subsidies. Moreover, shifting to electric vehicles (EVs) with alternative energy, primely renewable energy sources, is considered a promising alternative to decreasing dependence on fossil fuel consumption. The availability of a sufficient EV charging station infrastructure is determined as an appropriate strategy and rudimentary requirement to optimize the growth of EV users, especially in urban cities. This study aims to utilize the k-mean algorithm's clustering method to group and select a potential EV charging station location in Jakarta an urban city in Indonesia. This study proposed a method for advancing the layout location's comprehensive suitability. An iterative procedure determines the most suitable value for K as centroids. The K value is evaluated by cluster silhouette coefficient scores to acquire the optimized numeral of clusters. The results show that 95 potential locations are divided into 19 different groups. The suggested initial EV charging station location was selected and validated by silhouette coefficient scores. This research also presents the maps of the initially selected locations and clustering.

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1. INTRODUCTION

In several sectors, primary energy sources, e.g., transportation, household, industry, commercial, power plant, and others (construction, agriculture, and mining), are mainly based on fossil fuels [1]. In a developing country, heightened dependence on fossil fuels affected energy sustainability issues, greenhouse gas emissions, and increasing state budget allocation toward fuel subsidies [2]. Especially the transportation sector has consumed elevated fossil fuels and contributes to a significant consequence to the environment. Moving to an alternative energy source in transportation could decrease carbon emissions. The energy transition to renewable energy sources (RES) has become a global issue in response to managing the threat of greenhouse gas emissions [3]. The electric vehicle (EV) is considered a promising option to minimize environmental impact and decrease addiction to fossil fuel consumption at once.

Nowadays, EV penetration and adoption in Indonesia as a developing country is very early. On the other hand, EV in Indonesia has great potential to mitigate greenhouse gas emissions and improve energy security. The extensive scale development of EVs is related to charging station infrastructure planning, technical aspects, economy, environment, social, and government policy support. Some research shows challenges and opportunities in the EV transition in the Indonesian context. Prasetio *et al*. [4] indicated that Indonesian are mainly sensitive to travel time and congestion when selecting their transportation mode. Gunawan *et al*. [5] suggested that the attitude toward use (ATU) factor by effort expectancies and performance, price value, hedonic motivation, operational, social, and financial risks influence EVs in Indonesia. The results indicate that only financial risk factors and perceived operational break customer intentions to use EVs. Novizayanti *et al*. [6] revealed that the innovation and social media effect allows a new perspective on assessing EV adoption in Indonesia. The cost-benefit analysis [7] indicates that generally, the longer and higher usage span of EVs ownership led to an additionally competitive total cost of ownership (TCO) than internal combustion engine (ICE) in Indonesia. If the fuel price rises, EV customers will have a lower TCO and become more adorable if the fuel price rises. From a battery storage point of view, Indonesia is one of the largest nickel ore providers as a critical element for EVs applications. Pandyaswargo *et al*. [8] revealed that infrastructure, technology, investment, pricing, compliance standards, and policy are the essential factors supporting the Indonesian battery industry. As early EV users, Indonesia faced problems determining the charging system infrastructure (conductive, inductive, or battery exchange). Indonesia needs a standard to select a suitable charging system and guide EV charging station infrastructure development [9].

Sufficient EV charging station availability is determined as a rudimentary prerequisite and suitable strategy to optimize the growth of private and public EV users. There are numerous optimal allocation methods for EV charging station infrastructures. Xi *et al*. [10] defined the charger location using a simulation–optimization model, criterion, and available budget. Lee *et al*. [11] were concerned with the charging behavior in California and examined the infrastructure location through charging station location (e.g., at the residential, office, or in the public area), level of charging (slow or fast charging), preferences, trip patterns, socio-demographic (e.g., gender or age), access, commute demeanor, vehicle characteristics, and charger workplace availability as influential factors. Guo and Zhao [12] employed a multi-criteria decision-making (MCDM) method through the fuzzy technique for others' preference by similarity to the ideal solution (TOPSIS) to consider EV charging station selection.

Data mining is dragging and locating patterns in big data sets and applying methods at the intersection of statistics, machine learning, and database systems. EV modeling based on data mining has been increasing in the last decade. The open datasets can use to support reproducible research in the EVs field [13]. The data mining approach in EVs research is founded on numerous pieces of literature. Trinko *et al*. [14] interpret and analyzes the charging price information from EVs charging data platform (the charging level, prices, geographic location, location type, network, and provider based on an ad hoc text mining method. Wang *et al*. [15] utilized the natural language processing (NLP) technique for investigating consumer preferences in EV charger infrastructure based on public social media posts. Almaghrebi *et al*. [16] analyzed user charging behavior to support efficiently managing the electrical grid employing the regression method XGBoost. Chen *et al*. [17] modeled the staying time, arrival time, and charging capacity data based on ternary symmetric kernel density estimation (KDE) for EV charging behaviors and load modeling. The power grid's charging impacts the planning and charging strategy for EV charging infrastructure.

The clustering algorithm is an unsupervised learning model and data analysis to discover hidden patterns in datasets. This technique clusters similar data points in a group and very different data points into distinct groups. This method is founded in several EV research fields, especially charging station planning. Shukla *et al*. [18] utilized K-mean and fuzzy C-means clustering to analyze the locations confined to the fast-charging station (FCS) by estimating EVs' service radius and energy consumption. Andrenacci *et al*. [19] employed fuzzy cluster analysis on private and conventional EV usage in metropolitan areas and carried out and aggregated a strategy for the optimal allocation of EV charger infrastructures using driving patterns. Shahriar and Al-Ali [20] analyzed the EV charging behavior and activity in the USA's public EV charger infrastructure as a consequence of the COVID-19 pandemic using hierarchical clustering, K-means, and Gaussian mixture models.

This study aims to utilize the K-mean algorithm and silhouette scores as clustering methods and evaluation for optimal location selection of EV charging infrastructure in Jakarta, Indonesia, an urban city in a developing country. The approach presented in this study is how to advance the comprehensive suitability of the layout location. The study is organized as follows: Section 2 presents an overview of Indonesia's current electric vehicle situation, location criteria, clustering method, and research methodology. The results of the analysis are reported in section 3. The simulation results and discussion are in section 4, and last but not least, the conclusions are in section 5.

2. MATERIAL AND METHOD

This section will explain the current situation of the transportation sector in Indonesia, especially in Jakarta's capital city. This city is the broadest and most populous urban accumulation in Indonesia, where the number of vehicles is growing consistently. So do EV users; it needs to be robust and accessible to support the sustainable growth of EVs user. The public EV charging location is one of the most essential for enhancing the number of EVs. The initial location selection will be based on potential areas. The clustering technique uses the K-means algorithm and the evaluation method uses the silhouette coefficient (SC).

2.1. Sector condition

Indonesia Statistics (BPS), a non-departmental government institute of Indonesia, shows the vehicle population was more than 136 million units in 2020 from the previous 2018 of 133 million units, as shown in Figure 1. The accumulation increase in vehicles consists of the following types: cars, buses, good vehicles, and motorcycles. The automotive market size in Indonesia is still growing consistently. The number of vehicles has increased dramatically compared to 2015, dominated by motorcycle growth. Fevriera *et al*. [21] found that the likelihood of motorcycle preference compared to other transportation modes is more raised by individuals living than in different ways, and motorcycle usage is most susceptible to travel length. However, vehicles based on ICE also produce harmful emissions [22].

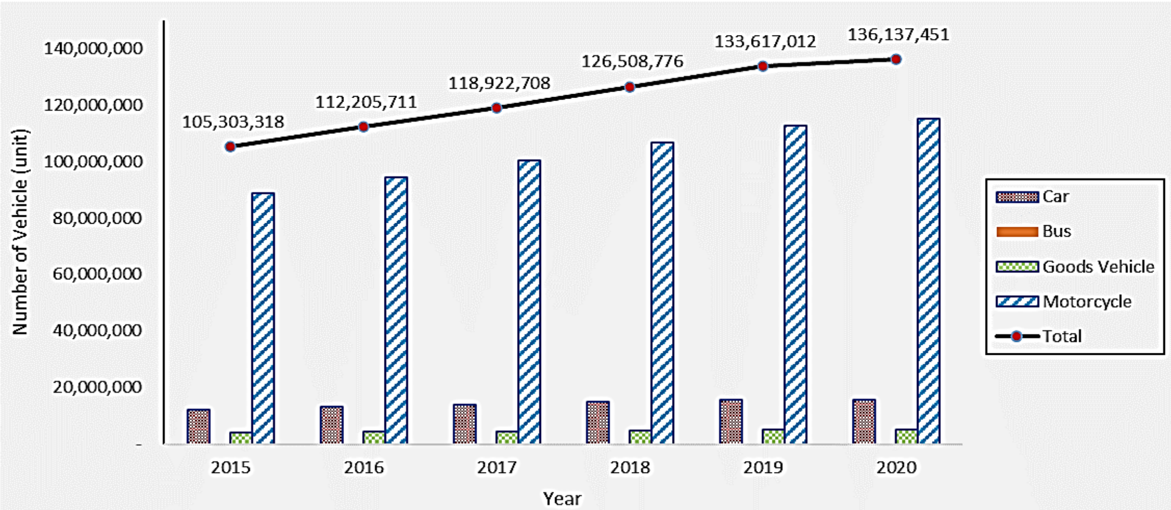


Figure 1. The number of vehicles by type in Indonesia from 2015 to 2020 [23]

On the other hand, Indonesia has decreased oil production and growing consumption [24]. The government regulates the fuel price. This condition leads to fiscal pressure because of an increase in fuel subsidies [25]. In the context of EVs transition, due to its market size and fuel subsidies, Indonesia has the potential to adopt EVs technology in the future transportation sector.

Table 1. The retail petrol stations and the population in the Jakarta area [26]

Administrative Cities*	Retail Petrol Station	Population in 2021 (in thousands)
North Jakarta	53	1,784.75
Central Jakarta	30	1,066.46
West Jakarta	64	2,440.07
East Jakarta	89	3,056.30
South Jakarta	83	2,233.86
Total	319	10,581.44

* Exclude the thousand islands regency, a chain of islands to the north of the coast

Jakarta is the special capital region of Indonesia. This city has the broadest and most populous urban accumulation. Jakarta calculated over 10.5 million people during the 2021 census, as shown in Table 1. Due to meeting the transportation need, the number of vehicles in Jakarta is still growing consistently. BPS was reported in the last three years at 20 million units in 2020, significantly increasing from the previous number of 11 million units. The extensive number of vehicles has risen dramatically, dominated by motorcycles, as shown in Figure 2. Table 1 also shows the registered number of *Stasiun Pengisian Bahan Bakar Umum* (SPBU) or petrol stations to serve the massive vehicle in Jakarta. There are about 319 petrol stations spread over the cities. Most users in most situations can quickly locate a petrol station and not wait in the line queue. The same dynamics will make the emerging grid of EV chargers' infrastructure in the future of Indonesian transportation.

The Indonesian government published Presidential Decree number 55 of 2019 regarding the acceleration of battery-based electric motor vehicles (*kendaraan bermotor listrik berbasis baterai* or KBLBB) as one of Indonesia's energy transition strategies. The government set an achievement target of 2 million EVs by 2025. These targets expect to reduce dependency on oil imports, support the national battery manufacturing industry, improve Indonesia's fiscal position, and enhance socio-economic development. To ensure the mark, PT PLN (Persero) as the state electricity utility will increase the number of EV public charging stations (*stasiun pengisian kendaraan listrik umum* or SPKLU) to accelerate the growth of EV. The EV penetration target needs to be attended to by the availability of EV charging infrastructure. The cumulative SPKLU has reached 267 units spread over 195 locations (public places such as offices, hotels, shopping centers, parking areas, petrol stations, and rest areas along toll roads).

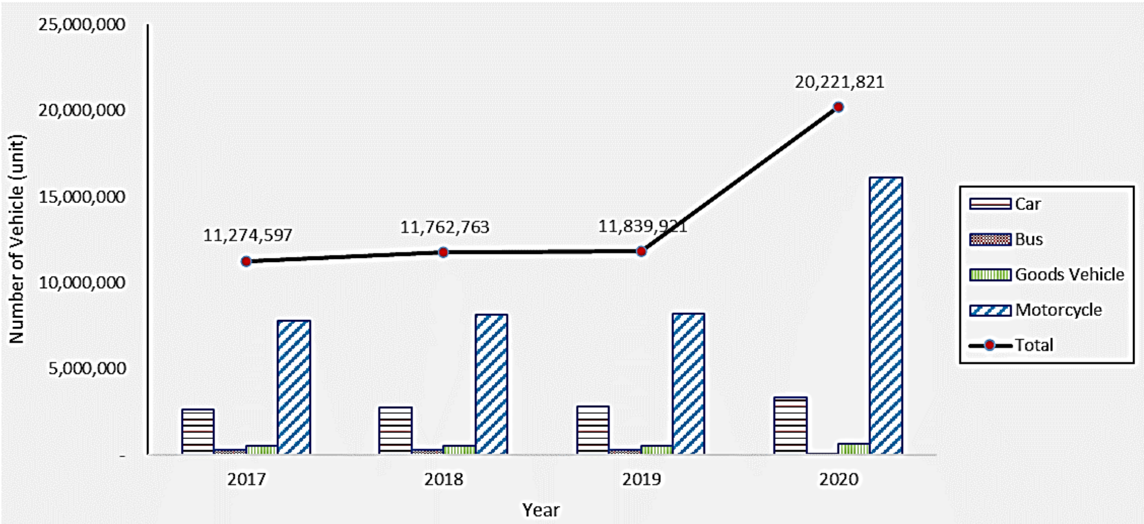


Figure 2. The number of vehicles by type in Jakarta as an Indonesian urban city from 2017 to 2020 [27]

The EVs charging infrastructure has aligned with a common standard protocol with a hierarchy for charging stations: location, port, and connector. The station location is a site with one or more EV ports at the exact location. Examples include a shopping mall, public transportation, parking lot, and recreation area. An EVs port provides power to charge EVs at a time even though it may have multiple connectors. A connector is plugged into a vehicle to charge it. On the regulation provisions, Number 13 of 2020 of the Indonesia Ministry of Energy and Mineral Resources (also known as KESDM), The EV charging technologies are as follows: Level 1 (slow charging with ≤ 3.7 kW output), level 2 (medium charging with ≤ 22 kW output), level 3 (fast charging with output ≤ 50 kW), and level 4 (ultrafast charging with output above 50 kW). SPKLU, as a public EV charger, consists of 3 connector types are as follows: Type 2 alternating current (AC) system, direct current (DC) charging system of AA series, and combined charging system (CCS) of FF series.

Figure 3 shows the 200-kW ultrafast charging technology installed in Bali, Indonesia. The number of Indonesia EVs will likely rise substantially in the future, and most of the charging will occur in residences. In order to accommodate this phenomenon, the availability of charging station infrastructure will be critical to support EV growth, especially away from home or workplace.

The modern petrol station evolved out of constant adaptation to the market and regulatory shifts, while today, EVs transform to develop the 'new norm' in terms of transportation aspects. However, with ultra-fast charging technology, consumers can charge their EVs in minutes. Today, modern fuel petrol stations in Jakarta offer the potential of charging infrastructure and maintaining their dominant societal position. Petrol stations are already strategically placed in locations according to driving patterns. There is no need for significant modifications in layout, but customers are likely to spend more time charging EVs than when filling petrol. Petrol station owners must determine the number of charging points and the capacity required for those EV chargers. The chargers can power by 100% renewable energy certificates (RECs).

Figure 3. The EVs ultra-fast charging in Indonesia

2.2. Selection

EV charging station needs to be robust and accessible to support the sustainable growth of EVs user. Whether utilized at dedicated charging stations or public access, public EV charging is any station that allows the general public to charge their vehicles. The location selection of public EV charging stations is one of the most critical topics for enhancing the use of EVs. Numerous kinds of literature have conducted methods for EVs location selection based on many considerations, as shown in Table 2. The existing research is considered to select the criteria that affect the charging station location. Most studies considered the primary measures of the economic, electrical power system, and driving range aspects. In the location selection process, a critical issue is how to address the most optimal location and quantity.

Table 2. Location selection method comparison of EVs charging station infrastructure

Research	Selection Method	Consideration
[6], [28]	Agent-based model	Patterns in residential EVs ownership and driving activities.
[12], [29], [30]	TOPSIS	Environment, economy, society, electric power system, and transportation system.
[31], [32]	p-median	Socio-demographic and spatial.
[33], [34]	Genetic algorithm (GA)	Investment of charging station operators, the travel costs, and total cost.
[35], [36]	Bi-level programming	Driving range, range anxiety, and distance convenience.
[37]	Mixed-integer non-linear (MINLP)	Development cost, energy loss, electric gird loss.
[38]–[40]	Bender’s decomposition algorithm	Vehicle miles traveled, total cost, price, facility locations, and origin-destination routes.
[41]	Multi-period optimization model	Demand profile and number of charging stations.
[42]	Integrated optimization	Operators, vehicles, drivers, power grid, and traffic flow.
[43]	Interpretive structural modeling (ISM) and fuzzy cross-impact matrix multiplication applied to classification (FMICMAC)	Charging demand, operating economy, traffic convenience, construction feasibility, and power grid security.
[44]	Game theory	Views of surrounding residents, government planning, distribution of electric vehicles around, traffic conditions, land use situation, weather conditions, geographical conditions, station harmonic pollution problem, fire-proof and explosion-proof conditions, electricity grid situation, total investment costs, station load and charging pattern, management & operation mode, and running cost per year.
[45], [46]	MCDM	Natural, economic, technical, and social criteria.
[47]	Analytical hierarchy process (AHP) - Geographic Information System (GIS)	Environmental impact and accessibility.

Figure 4 shows Jakarta’s administrative cities named Jakarta, Bogor, Depok, Tangerang, and Bekasi (Jabodetabek). Also, the maps represent the spatial expedience distribution of clustering. This study focused only on Jakarta’s administrative cities (North Jakarta, Central Jakarta, West Jakarta, East Jakarta, and South Jakarta). The criteria are considered to determine clustering that affects the charging location. In this research, some essential criteria are used to determine the early-stage EV charging station locations, as shown in Table 3. The proposed area that fulfills the requirements is about 95 priority locations, and overall detailed locations are provided in Table 4.

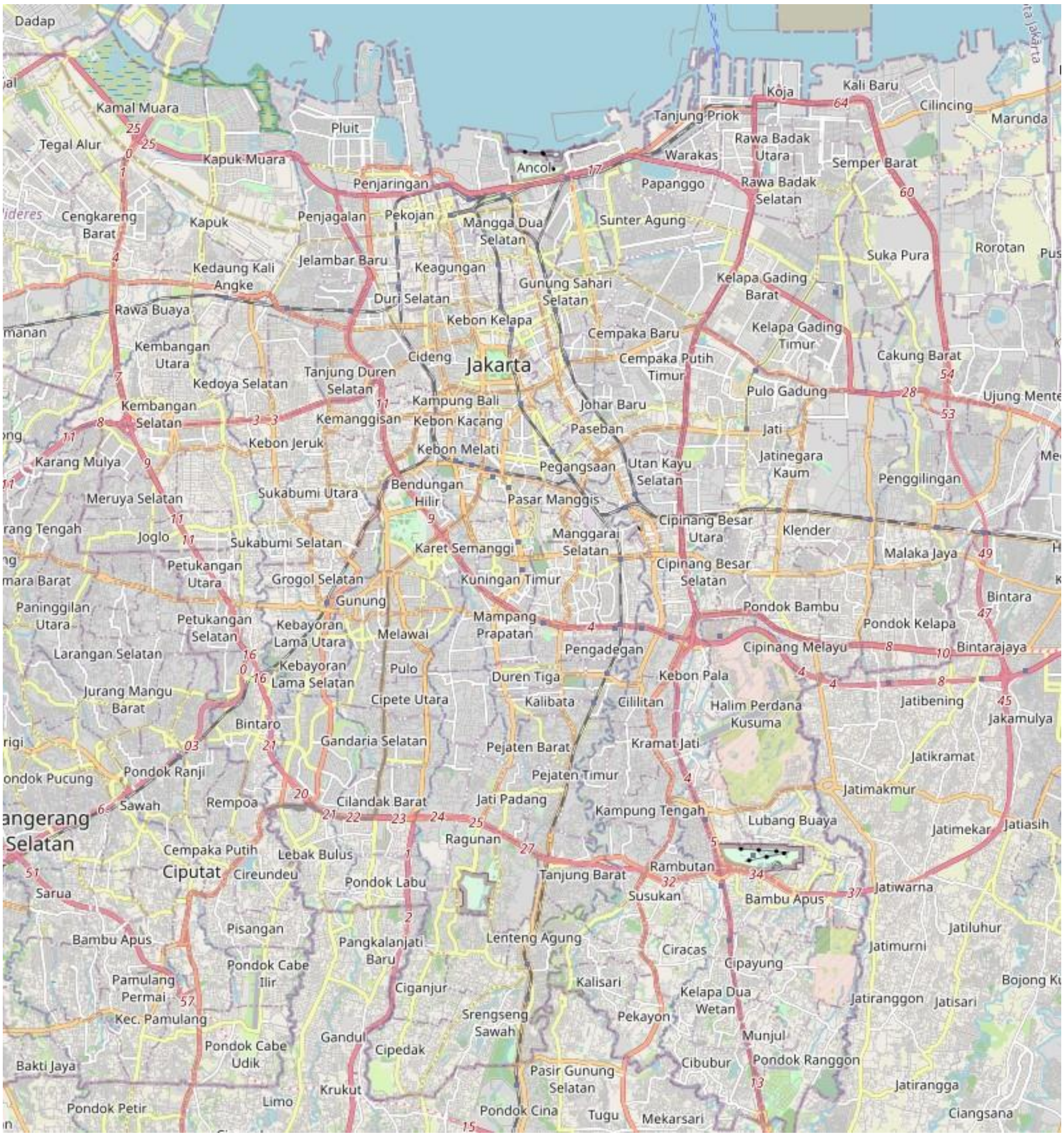


Figure 4. Jakarta and its administrative cities

Table 3. Criteria selection of EVs charging station infrastructure

Criteria	Description of Criteria
Shopping malls [48], [49]	Department stores usually anchor large indoor shopping centers or pedestrian promenades. Shopping malls can deliver activities and experiences (i.e., promotions, shopping, entertainment, social gatherings, performances, festivals, product launches, and many more).
Public transportation area [50]	The passengers-by-group travel systems available for the general public transportation system are typically managed on a schedule, charged for each trip—for example, bus stations, airports, & railway stations, and operated on established routes.
Parking lots [51], [52]	This criterion is a dedicated area intended for vehicle parking.
Recreation area [53]	Public recreational areas are land designed, constructed, or used for recreational activities such as zoos, sports stadiums, spacious gardens, coasts, museums, monuments, and other indoor or outdoor recreational areas.

Table 4. Proposed location of EV charging station infrastructure in Jakarta, Indonesia

Location*	Latitude	Longitude	Location*	Latitude	Longitude	Location*	Latitude	Longitude
Location 1	-6,176594596	106,8411911	Location 33	-6,291227552	106,8821037	Location 65	-6,209383854	106,8470437
Location 2	-6,160725397	106,8187810	Location 34	-6,199948110	106,8906452	Location 66	-6,224449693	106,8104337
Location 3	-6,195169429	106,8204305	Location 35	-6,221688898	106,9317479	Location 67	-6,245506735	106,8022381
Location 4	-6,137018428	106,8242818	Location 36	-6,270502248	106,8677406	Location 68	-6,244546861	106,8006717
Location 5	-6,164650429	106,8774630	Location 37	-6,216210199	106,8647847	Location 69	-6,244098923	106,7975604
Location 6	-6,166352996	106,8030494	Location 38	-6,262352825	106,8656816	Location 70	-6,243725632	106,8030213
Location 7	-6,137010631	106,8243441	Location 39	-6,183446194	106,9149524	Location 71	-6,256246970	106,8521761
Location 8	-6,138589285	106,8316260	Location 40	-6,243927306	106,8693384	Location 72	-6,257297463	106,8559902
Location 9	-6,224663229	106,8038949	Location 41	-6,312761087	106,8618696	Location 73	-6,301428301	106,8140018
Location 10	-6,187792300	106,8363946	Location 42	-6,340067885	106,8900464	Location 74	-6,224059695	106,8267484
Location 11	-6,196747329	106,8288394	Location 43	-6,369019483	106,8935648	Location 75	-6,224464649	106,8228699
Location 12	-6,155099120	106,8488322	Location 44	-6,217889134	106,9242029	Location 76	-6,224583199	106,8296034
Location 13	-6,176669262	106,8411911	Location 45	-6,194039012	106,8904845	Location 77	-6,223340527	106,8426469
Location 14	-6,188924265	106,8117381	Location 46	-6,187630886	106,7396061	Location 78	-6,220531158	106,7838153
Location 15	-6,225480061	106,7993066	Location 47	-6,189249063	106,7965048	Location 79	-6,224103629	106,8266598
Location 16	-6,193979227	106,8222158	Location 48	-6,153361538	106,7961210	Location 80	-6,264299260	106,7990403
Location 17	-6,188202763	106,8241371	Location 49	-6,188276629	106,7379007	Location 81	-6,244211191	106,7835505
Location 18	-6,226767458	106,7977927	Location 50	-6,139976181	106,7315487	Location 82	-6,217989963	106,8350578
Location 19	-6,194068862	106,8163898	Location 51	-6,178551096	106,7921913	Location 83	-6,208852493	106,8180235
Location 20	-6,134548098	106,8310215	Location 52	-6,188183897	106,7341763	Location 84	-6,224401289	106,8231954
Location 21	-6,157287929	106,9084263	Location 53	-6,151233763	106,7146056	Location 85	-6,291442160	106,7991749
Location 22	-6,116446163	106,7896404	Location 54	-6,168576242	106,7866714	Location 86	-6,175477728	106,8271743
Location 23	-6,126387128	106,7911850	Location 55	-6,146658730	106,8238147	Location 87	-6,135157326	106,8132464
Location 24	-6,137964328	106,8708355	Location 56	-6,146189366	106,8163367	Location 88	-6,128425415	106,8335235
Location 25	-6,151508231	106,8918734	Location 57	-6,142376730	106,8154595	Location 89	-6,119293938	106,8501746
Location 26	-6,136331329	106,8218297	Location 58	-6,142352058	106,8166404	Location 90	-6,302371247	106,8951881
Location 27	-6,151508231	106,8918520	Location 59	-6,177368596	106,7906508	Location 91	-6,119150604	106,6746772
Location 28	-6,145759989	106,8918469	Location 60	-6,215129622	106,8299823	Location 92	-6,265183076	106,8859388
Location 29	-6,160560380	106,9062484	Location 61	-6,265569090	106,7843283	Location 93	-6,335181836	106,7640609
Location 30	-6,122513860	106,9158798	Location 62	-6,289869567	106,7781242	Location 94	-6,219126562	106,8045524
Location 31	-6,127220163	106,7911950	Location 63	-6,219982427	106,8144625	Location 95	-6,312464977	106,8200396
Location 32	-6,107747467	106,7791958	Location 64	-6,280386318	106,8288895			

* Exclude the thousand islands regency, a chain of islands to the north of the coast.

2.3. Algorithm and silhouette coefficient

Organizing data into suitable groupings is fundamental to understanding and learning the data. Several popular clustering algorithms include k-medoids [54], hierarchical clustering [55], hidden Markov models [56], self-organizing maps [57], fuzzy C-means clustering [58], and K-means [59]. K-means is an unsupervised technique of clustering dataset groups into K clusters in which the nearest mean of separate compliance belongs to the set [60].

Figure 5 shows the basic clustering construction with the K-means method using the dataset's similarity and dissimilarity (based on distance). Figure 5(a) shows the input dataset and the selected cluster's initial representatives (centroid). The K value represents the number of centroids in collected data. A centroid is the proposed location describing the cluster's compromise.

The initial centroid is selected unsystematically and subsequently chosen from the remaining data points with likelihood proportioned to the squared length from the nearest centroid. The pre-defined K clusters (K=4) are randomly generated by associating the dataset with the nearest mean. After that, it computes the distance of each data with the most petite length and repeats iteration until convergence, as shown in Figure 5(b), and the group is evaluated until it reaches the optimal number of the set (K=6), as shown in Figure 5(c). K-means method utilizes the data point i in the cluster C_i ($i \in C_i$) follows (1), where $a(i)$ is the average distance between data point i and all data points in its cluster (C_i) [61].

$$a(i) = \frac{1}{|C_i|} \sum_{j \in C_i, i \neq j} d(i,j) \tag{1}$$

Furthermore, $b(i)$ is the minimum average distance between data point i to all data points in any other clusters (C_k) that not containing data point i ($C_k \neq C_i$) as shown in (2). The shorter average distance of data point i to all points in any other cluster indicates that data point i is not a cluster member—the cluster with this slight mean dissimilarity or neighboring cluster of data points i.

$$b(i) = \min_{k \neq i} \frac{1}{|C_k|} \sum_{j \in C_k} d(i,j) \tag{2}$$

There are numerous methods to evaluate the clustering performance metrics, such as rand index [62], adjusted rand index [63], mutual information [64], Calinski-Harabasz index [65], Davies-Bouldin index [66], and silhouette score [58]. One of the evaluation indicators is the SC which assesses the cluster validity based on the measure of the average distance between one data point and other data points in the same cluster (cohesion) and the average distance among different clusters (separation). The SC contains the individual SC and cluster SC (CSC). The individual SC $s(i)$ is shown in (3), which indicates how closely the data point is grouped in that cluster.

$$s(i) = \frac{b(i)-a(i)}{max\{a(i)b(i)\}} \tag{3}$$

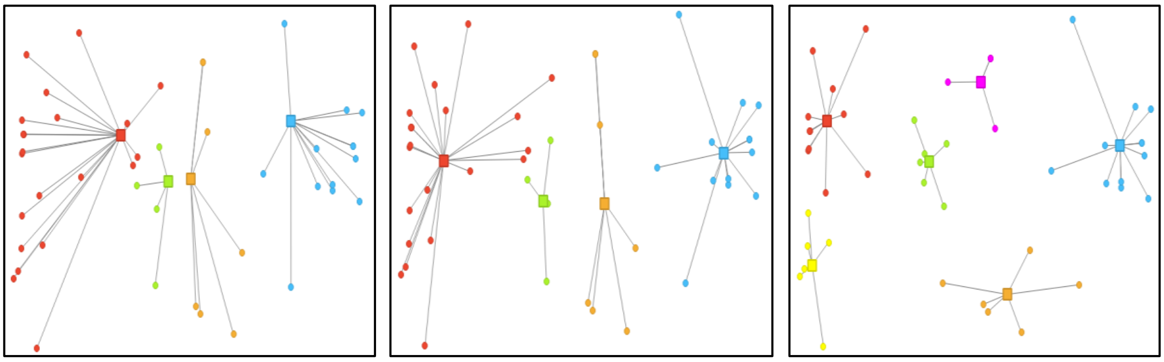
The CSC for expression outline is shown in (4). The optimal number of clusters K is the one that maximizes the silhouette scores over a range of possible scores for K. The scores measure how similar a data point is within the cluster (cohesion) compared to other clusters (separation).

$$s(i,n) = \frac{1}{n}\sum_{i=1}^{n} s(i) \tag{4}$$

The SC $s(i)$ and CSC scores $s(i,n)$ can vary between -1 and 1, as shown in (5) and (6). For each data point i, $s(i)$ can range between -1 and 1. If $s(i)$ is close to 1, it means $a(i)$ is much smaller than $b(i)$, so the data point is assigned to a suitable cluster. But when $s(i)$ is about 0, then $a(i)$ and $b(i)$ are approximately equal. When $s(i)$ is close to -1, $a(i)$ is much larger than $b(i)$, so the data point i is closer to the other cluster.

$$1 \le s(i) \le 1 \tag{5}$$

$$1 \le s(i,n) \le 1 \tag{6}$$



(a) (b) (c)

Figure 1. K-means basic process based on data distance: (a) the input dataset and initial centroid as a learning problem, (b) the evaluation of the distance and repeat iterations, and (c) the calculation of new cluster membership

3. RESULTS

An iterative procedure determines the best value for K center points or centroids. The average distances were calculated to the centroid across all locations for each K value. This research uses a dataset with 95 data points; the CSC scores were obtained by changing the value of K from 2 to 30, as shown in Figure 6. Assigns each data point to its nearest centroid. Those data points which are near the particular centroid construct a cluster. The simulation results show the cluster's scores below 5 are a poor selection for the provided datasets due to groups with below-average silhouette scores and broad fluctuations in the measure of the silhouette plots. The silhouette analysis reveals the CSC score is maximized at K=19. It indicates the optimal location clustering is 19 different groups.

The SC scores can examine the cohesion length between the selected cluster. The silhouette evaluation reveals how tight each data pinpoint is in one collection. This evaluation result has a range of -1 to 1. In clusters 1, 2. 13, and 17, there are different data points with negative scores of almost 0 in optimum K, as shown in Figure 7. A negative score of nearly 0 implies overlapping groupings very near the decision border of the neighboring groups. The higher CSC scores suggest that the data points are optimally positioned.

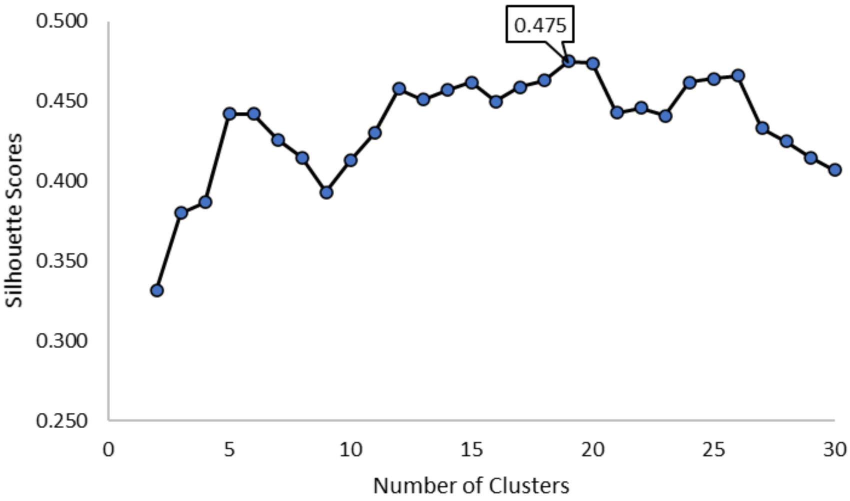


Figure 6. The number of K-means clusters and cluster silhouette scores

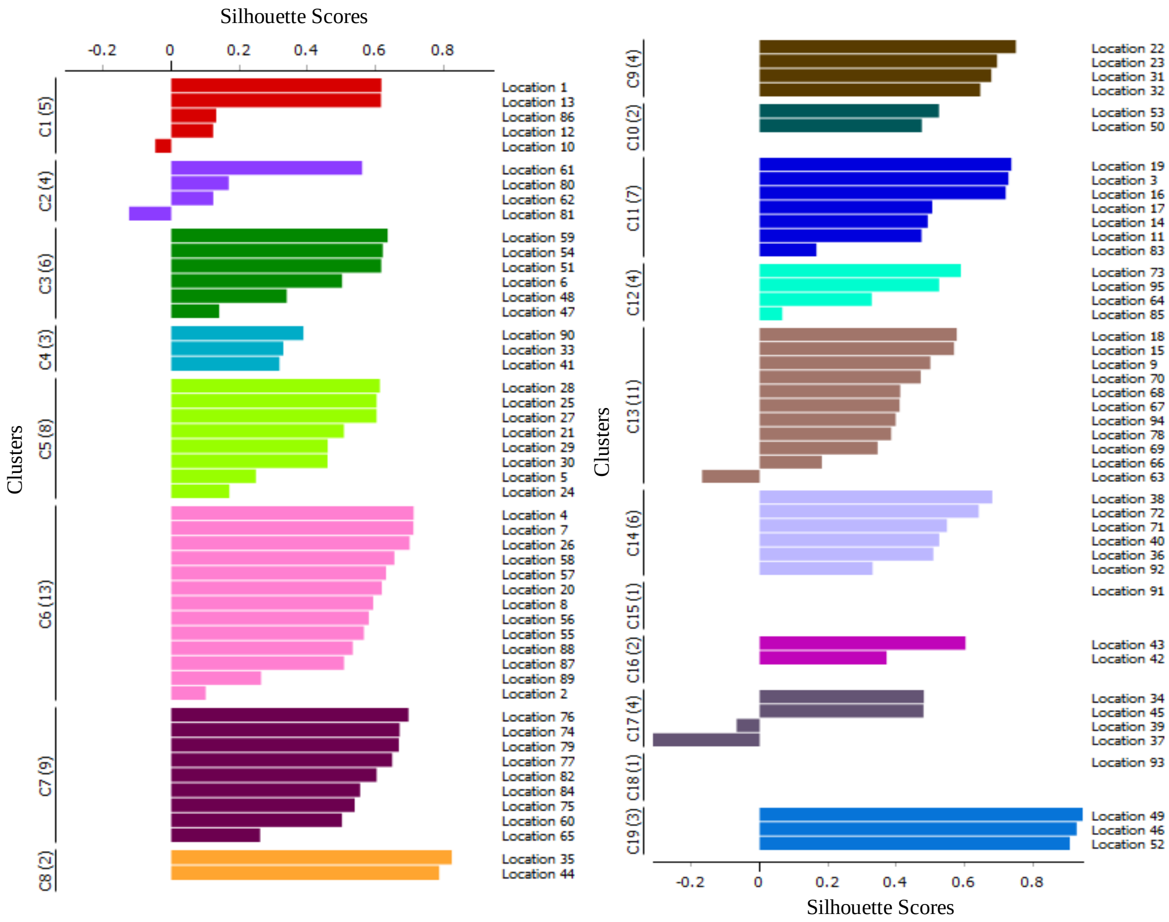


Figure 7. The silhouette scores in each cluster are based on the K-means algorithm

The K-means method resulted in 19 optimal clusters for the initial EV charging station location in Jakarta an urban city in Indonesia. The distribution frequency or member of each cluster is shown in Figure 8. The highest distribution frequency is in cluster 6 with 13 potential locations, and the lowest is in clusters 15 and 18 with only one proposed location. A distant location from other clusters causes the lowest cluster membership.

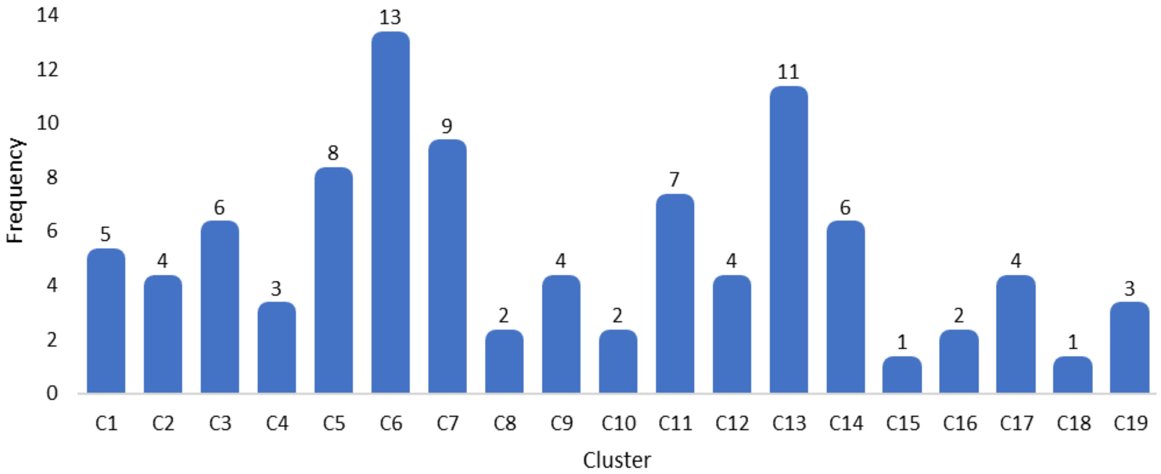


Figure 8. The amount member in each group is based on the K-means method

The cluster members have been presented in different colors and sizes as shown in Figure 9. The colors indicate the location is in the same cluster, while the size suggests the silhouette score. Nevertheless, current results indicate that the proposed cluster selection algorithm and the process are validated.

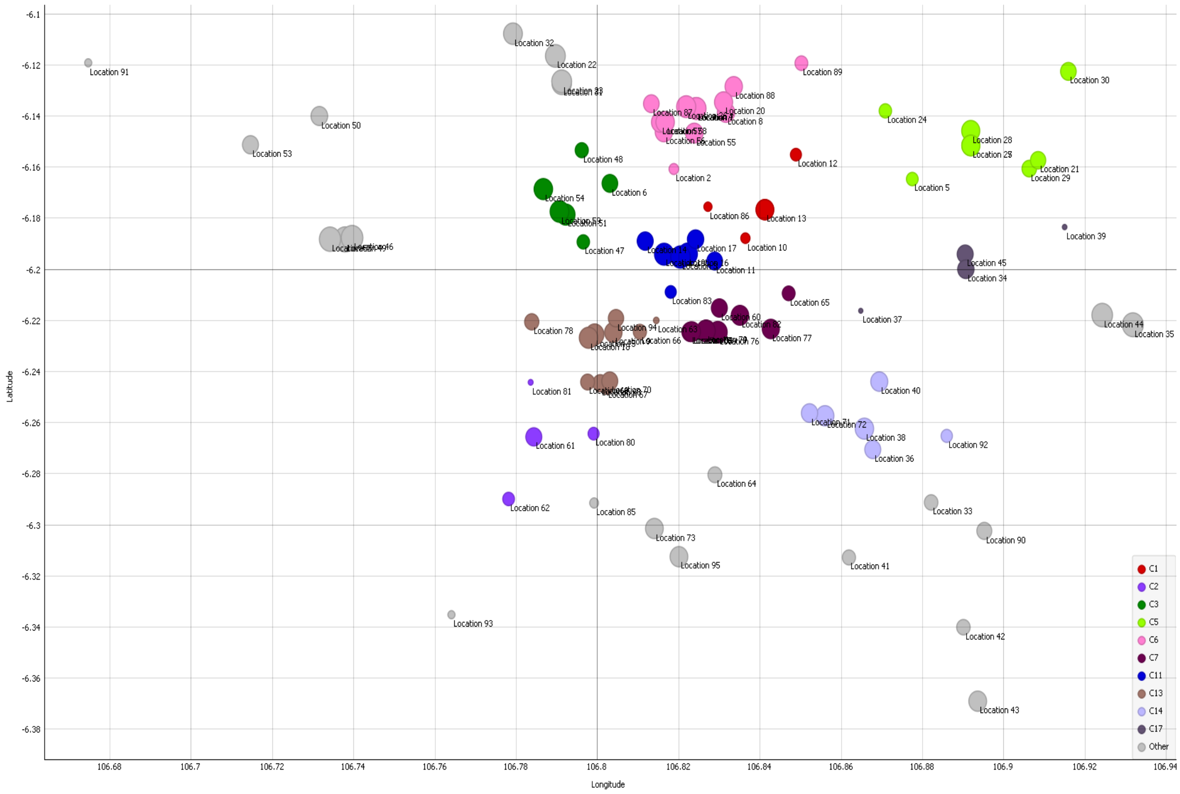


Figure 9. The clustering results in simple grid structure maps based on the K-means method

The simulation results are then combined on a map to see proposed EV charging infrastructure locations based on their clustering area, as shown in Figure 10. The data point with the most elevated SC scores is chosen from an individual site to represent the cluster, as shown in Table 5.

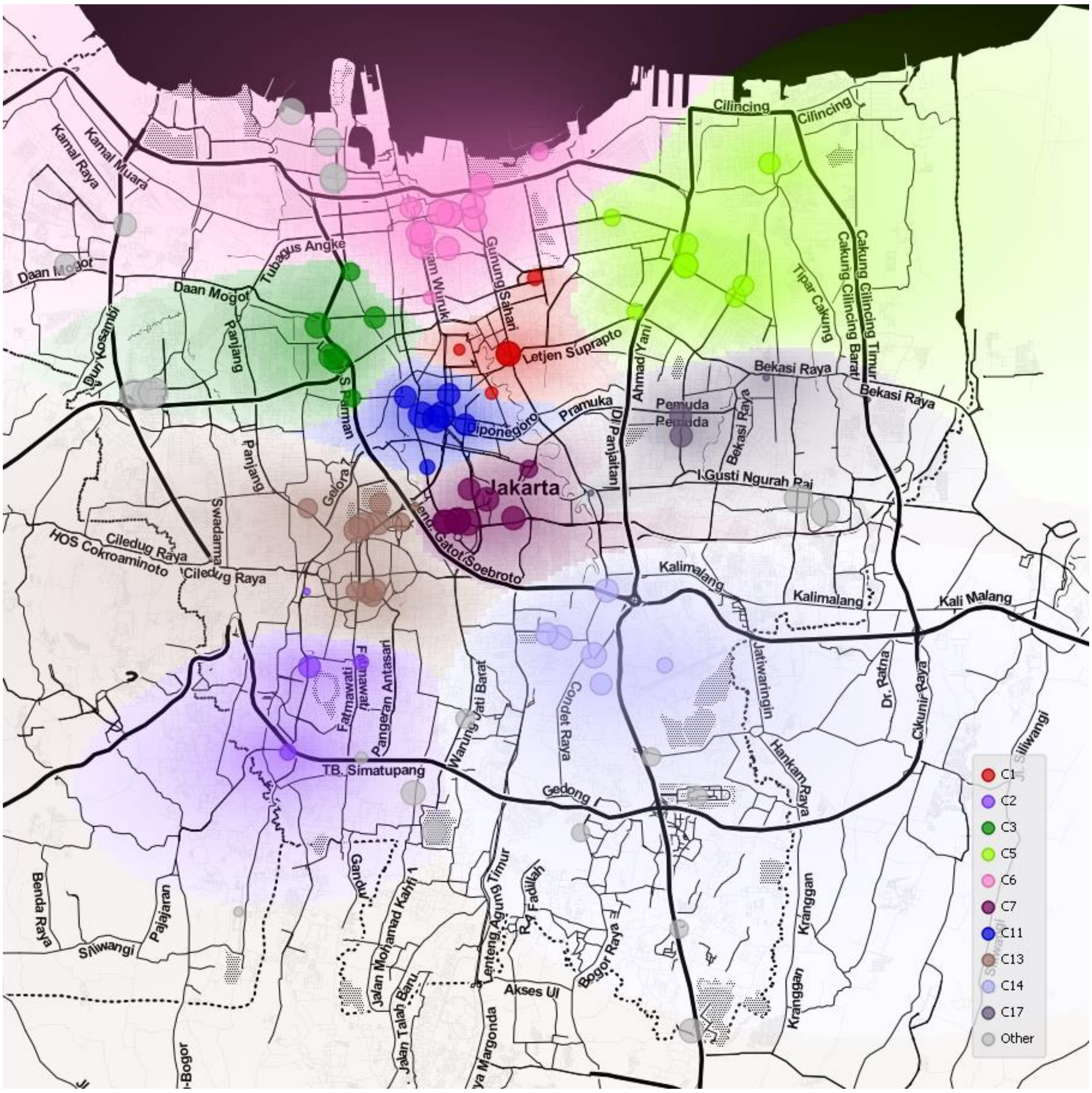


Figure 10. Initial location covering maps in Jakarta administrative cities based on the K-means algorithm

Table 5. Suggested locations of initial EVs charging station location in Jakarta based on SC scores

Cluster	Location*	Latitude	Longitude	Silhouette
Cluster 1	Location 1	-6,176594596	106,8411911	0,668829432
Cluster 2	Location 61	-6,265569089	106,7843283	0,642949392
Cluster 3	Location 59	-6,177368596	106,7906508	0,685267476
Cluster 4	Location 90	-6,302371247	106,8951881	0,624243228
Cluster 5	Location 28	-6,145759989	106,8918469	0,678410488
Cluster 6	Location 4	-6,137018428	106,8242818	0,694316814
Cluster 7	Location 76	-6,224583199	106,8296034	0,688492219
Cluster 8	Location 35	-6,221688898	106,9317479	0,720907898
Cluster 9	Location 22	-6,116446163	106,7896404	0,706012211
Cluster 10	Location 53	-6,139976181	106,7315487	0,651079619
Cluster 11	Location 19	-6,194068862	106,8163898	0,694217443
Cluster 12	Location 73	-6,301428301	106,8140018	0,672021288
Cluster 13	Location 18	-6,226767458	106,7977927	0,681950564
Cluster 14	Location 38	-6,262352825	106,8656816	0,681969724
Cluster 15	Location 91	-6,119150604	106,6746772	0,500000000
Cluster 16	Location 43	-6,369019483	106,8935648	0,669645376
Cluster 17	Location 34	-6,19994811	106,8906452	0,646262356
Cluster 18	Location 93	-6,335181836	106,7640609	0,500000000
Cluster 19	Location 49	-6,188276629	106,7379007	0,738349124

* Exclude the thousand islands regency, a chain of islands to the north of the coast

4. DISCUSSION

The EV charging station infrastructure needs to sustain new EV users' growth. The initial location of public EV charger stations is one of the most crucial actions for enhancing the use of EVs. The K-mean clustering assigns 95 data points to its nearest centroid constructed into a suitable cluster. The CSC scores evaluate the value of K changes from 2 to 30. The simulation results suggest the optimal initial location of public EVs charging stations is 19 different clusters. The results reveal that the value of K below 5 is a below-average CSC score. The SC scores (range of -1 to 1) evaluate how close each data point is in one cluster. The simulation results show that clusters 1, 2. 13, and 17 found different data points with negative scores near 0 in the optimum value of K, which indicates very near the decision border of the neighboring groups. The higher CSC and SC scores suggest that the data points are suitable clusters. The K-means algorithm resulted in 19 clusters for the initial EV charging station location in Jakarta, an urban city in Indonesia. Cluster 6 is the highest distribution with 13 proposed sites, and clusters 15 and 18 with only one proposed location. Future research in this area can directly consider the capacities of the EV charger stations in each cluster; as the number of users increases in the future, the EV charger station capacity becomes critical.

5. CONCLUSION

The obtainable of a satisfactory EV charging station infrastructure is a rudimentary prerequisite and suitable strategy to optimize the growth of EV users in urban cities. Shifting to EVs is considered a promising alternative in developing countries. Decreasing dependence on fossil fuel consumption affected the decreasing state budget allocation towards fuel subsidies, greenhouse gas emissions, and energy sustainability issues. This study provides a practical technique using the K-mean algorithm's method to cluster and choose an initial EV charging station location based on the potential site in Jakarta, Indonesia. The criteria of priority location proposed in this paper are shopping centers, public transportation, parking, and recreation areas. An iterative algorithm determines the most suitable value for K as centroids. The optimal K value evaluates by CSC scores to acquire the numeral of groupings. The results show that the potential locations divide into 19 different groups spread in Jakarta administrative cities. Each cluster's suggested initial EV charging station was selected and validated by silhouette coefficient SC scores. Although some contributions have been made, this study still has limitations. Future work in this area can consider the capacities allocation of the EVs charger stations in each cluster, power system analysis, and economic aspects as the number of EVs users increases.

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