Volume 5, No. 7 July 2026
p-ISSN 2980-4868 | e-ISSN 2980-4841
https://ajesh.ph/index.php/gp

Data-Driven Classification of Public Electric Vehicle Charging Station Power Using K-Means Clustering: A Case Study in Jakarta, Indonesia

Nadhif Dzulfa, Iwa Garniwa
Universitas Indonesia
Email: nadhif.dzulfa@ui.ac.id, iwa@eng.ui.ac.id

Abstract

Keywords
electric vehicle; public charging station; charger power classification; K-Means Clustering; charging infrastructure.

The rapid growth of electric vehicles requires public charging infrastructure that is not only widely available but also properly classified according to its service capability. In Jakarta, Indonesia, the rated power of public electric vehicle charging stations varies widely from 7 kW to 480 kW, indicating diverse charging service levels. However, the existing fixed-threshold classification may not fully represent the actual distribution of charger power, particularly in the high-power segment where all chargers above 50 kW may be grouped into a single Ultra-Fast category. This study aims to classify the rated power of public EV charging stations in Jakarta using K-Means Clustering and compare the results with the existing power classification scheme. The analysis was conducted using 731 public charging station points, with rated power as the main clustering variable. The optimal number of clusters was evaluated using the Elbow Method and Silhouette Score. The results show four main clusters: Low Power at 7–40 kW, Mid Power at 47–74 kW, High Power at 100–120 kW, and Ultra High Power at 160–480 kW. The Low Power cluster dominates the dataset with 517 points or 70.7% of the total data. The findings indicate that chargers above 50 kW are not homogeneous and can be divided into more specific power segments. Therefore, data-driven classification can provide a more representative basis for charging station nomenclature, infrastructure mapping, and future charging infrastructure planning.

INTRODUCTION

The rapid growth of electric vehicles (EVs) has increased the need for reliable, accessible, and technically appropriate public charging infrastructure (International Energy Agency, 2024; International Energy Agency, 2025). Public EV charging stations play an important role in reducing range anxiety, supporting urban mobility, and accelerating EV adoption. As EV penetration increases, infrastructure planning should not only consider the number of charging points, but also the classification of charger power capacity, which is essential for service differentiation, infrastructure mapping, and future planning.

Charger power classification helps regulators, operators, investors, and users understand the service capability of charging stations (Arooj et al., 2025; Haces-Fernandez, 2023; Prakhar et al., 2026; Wady & Consoni, 2025). A clear classification system can distinguish charging levels, estimate charging time, and support infrastructure development strategies. However, when charger power ratings become increasingly diverse, a fixed-threshold classification may not fully represent the actual distribution of charger capacity in the field (Diaz-Londono et al., 2026; Haces-Fernandez, 2023; Mejjaouli et al., 2026).

Jakarta, Indonesia, provides an important case for evaluating public EV charging power classification because the rated power of public charging stations in the city varies widely, ranging from 7 kW to 480 kW. The existing classification generally divides charging stations into Standard, Medium, Fast, and Ultra-Fast charging (Ministry of Energy and Mineral Resources of the Republic of Indonesia, 2023). Although this classification is simple and easy to apply, it may oversimplify the actual variation of charger power, particularly in the high-power segment.

This condition highlights the need for a data-driven evaluation of charger power classification. A data-driven approach can identify natural groupings in the actual charger power distribution without relying solely on predefined thresholds (Pandey et al., 2026; Shirvani et al., 2025; Sun et al., 2025). Clustering methods are suitable for this purpose because they group numerical data based on similarity patterns. Among various clustering techniques, K-Means Clustering is widely used due to its simplicity, interpretability, and ability to produce clear cluster centroids (MacQueen, 1967; Lloyd, 1982; Jain, 2010; Ezugwu et al., 2022; Ezugwu et al., 2023). These centroids can represent typical power levels within the observed charging infrastructure data.

Previous studies on EV charging infrastructure have commonly focused on charging station placement, demand estimation, techno-economic analysis, grid impact, and smart charging strategies (Deb et al., 2018; Sadeghi-Barzani et al., 2014; Al-Dahabreh et al., 2023; Yuan et al., 2025). However, studies that specifically evaluate charger power classification using actual public charging station data remain limited. This gap is important because power classification is not only a regulatory label, but also a basis for infrastructure mapping, service differentiation, nomenclature standardization, and future projection.

The urgency of this research is underscored by Indonesia's national targets for EV adoption, which aim for 2.1 million two-wheeled EVs and 2,200 four-wheeled EVs by 2025. The Indonesian government has issued regulations to support EV charging infrastructure deployment, yet the classification of charging power remains based on fixed thresholds that may not reflect the actual diversity of charger capabilities in the field. The novelty of this study lies in its application of K-Means clustering to classify charger power in Jakarta, providing a data-driven alternative to the existing fixed-threshold classification system, particularly addressing the oversimplification of the high-power segment.

This study aims to classify the rated power of public EV charging stations in Jakarta using K-Means Clustering and to compare the resulting clusters with the existing charging power classification. The study uses a dataset of 731 public charging station points in Jakarta, with rated power as the main clustering variable. The optimal number of clusters is evaluated using the Elbow Method and Silhouette Score.

The main contributions of this study are twofold. First, it provides a data-driven classification of public EV charging station rated power based on actual infrastructure data in Jakarta. Second, it evaluates the limitations of the existing classification scheme, particularly in the high-power segment above 50 kW. The findings are expected to support the improvement of charging station nomenclature, infrastructure mapping, and future charging infrastructure planning in Indonesia.

METHOD

Research Design

This study used a quantitative approach based on secondary data. The research was designed to classify the rated power of public electric vehicle charging stations in Jakarta using K-Means Clustering and to compare the resulting clusters with the existing charging power classification. The focus of this study is the identification of natural power segments based on actual rated power data.

The research process consists of four main stages. First, public charging station data in Jakarta were collected and prepared. Second, descriptive statistical analysis was conducted to identify the distribution and variation of charger rated power. Third, K-Means Clustering was applied to classify charger rated power into several power groups. Fourth, the clustering results were compared with the existing charging power classification to evaluate whether the current classification represents the actual power distribution.

Study Area and Dataset

The study area is Jakarta, Indonesia. Jakarta was selected as the case study because it is one of the main urban centers in Indonesia and has a relatively high concentration of public electric vehicle charging infrastructure. The city also shows a wide variation in charger rated power, making it suitable for evaluating public charging station power classification.

The main dataset consists of 731 public electric vehicle charging station points located in Jakarta. The dataset includes information on station name, location or administrative area, charging mode, and rated power. In this study, the rated power of each charging station, expressed in kilowatts (kW), is used as the main clustering variable. The observed rated power ranges from 7 kW to 480 kW.

Existing Charging Power Classification

The existing charging power classification used in this study consists of four main categories: Standard (≤7 kW), Medium (>7-22kW), Fast (>22-50kW), and Ultra Fast charging (>50kW) [3]. The classification is based on rated power thresholds. In the dataset, the observed nominal power values are distributed across these categories as follows: Standard includes 7 kW; Medium includes 11 kW, 20 kW, and 22 kW; Fast includes 24 kW, 25 kW, 30 kW, 40 kW, 47 kW, and 50 kW; and Ultra Fast includes power values above 50 kW, such as 55 kW, 60 kW, 74 kW, 100 kW, 120 kW, 160 kW, 180 kW, 200 kW, and 480 kW.

This classification was used as a benchmark to evaluate whether the actual distribution of rated power in Jakarta follows the existing classification structure or forms different data-driven clusters.

Descriptive Statistical Analysis

Descriptive statistical analysis was conducted to understand the general characteristics of the rated power data. The analysis includes minimum value, maximum value, mean, median, mode, standard deviation, and frequency distribution. This step was used to identify dominant power values, data dispersion, and the presence of high-power charging stations.

The frequency distribution was also used to observe whether the rated power values are concentrated in certain nominal power levels or distributed continuously. This analysis provides an initial basis for understanding the need for clustering-based classification.

K-Means Clustering

K-Means Clustering was applied to classify charging station rated power into several clusters. The method groups data points based on similarity by minimizing the distance between each data point and its corresponding cluster centroid (MacQueen, 1967; Lloyd, 1982). In this study, the clustering process was performed using one numerical variable, namely charger rated power in kW.

The objective function of K-Means Clustering is to minimize the within-cluster sum of squares (WCSS), as shown in the following equation:

$$\mathrm{WCSS} = \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2$$

where (k) is the number of clusters, (C_i) is the (i)-th cluster, (x) is a data point, and (\mu_i) is the centroid of cluster (C_i). The centroid represents the average rated power of the data points assigned to each cluster.

Although only one variable was used, K-Means remains relevant because the objective of this study is specifically to classify charger power levels. The use of a single variable allows the resulting clusters to be directly interpreted as rated power segments and compared with the existing classification scheme.

Determination of the Number of Clusters

The number of clusters was evaluated using the Elbow Method and Silhouette Score. The Elbow Method was used to observe the reduction in WCSS as the number of clusters increases. A suitable number of clusters is indicated by the point where the decrease in WCSS begins to slow down.

The Silhouette Score was used to evaluate cluster compactness and separation (Rousseeuw, 1987). The score is expressed as:

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

where (a(i)) is the average distance between point (i) and other points in the same cluster, while (b(i)) is the average distance between point (i) and points in the nearest different cluster. A higher Silhouette Score indicates better cluster separation.

In this study, the number of clusters was tested from (k = 2) to (k = 10). The final number of clusters was selected by considering statistical performance, interpretability, and comparability with the existing four-category classification.

Comparison with Existing Classification

After the K-Means Clustering results were obtained, the resulting clusters were compared with the existing charging power classification. The comparison was conducted to identify similarities and differences between the fixed-threshold classification and the data-driven classification.

The comparison focused particularly on the high-power segment, where the existing classification groups all charging stations above 50 kW into a single Ultra Fast category. The clustering results were used to evaluate whether this category represents a homogeneous power group or consists of several distinct power segments.

Research Limitation

This study has several limitations. First, the analysis is based on secondary data and does not include real charging transaction data such as charging duration, energy delivered, number of sessions, and charger occupancy rate. Second, the clustering process uses only charger rated power as the clustering variable. Other factors such as spatial location, traffic demand, grid capacity, vehicle characteristics, and user behavior are not included in the clustering model. These limitations can be addressed in future studies by integrating transaction data, spatial analysis, grid readiness assessment, and alternative clustering methods.

RESULTS AND DISCUSSION

Descriptive Characteristics of Charging Station Power

The dataset consists of 731 public EV charging station points in Jakarta. The rated power values range from 7 kW to 480 kW, indicating a wide variation in public charging infrastructure capacity. A total of 19 unique rated power values were identified, namely 7, 11, 20, 22, 24, 25, 30, 40, 47, 50, 55, 60, 74, 100, 120, 160, 180, 200, and 480 kW.

The descriptive statistics show that the mean rated power is 42.09 kW, while the median and mode are both 22 kW. The mode value of 22 kW dominates the dataset, with 418 charging station points or 57.2% of the total data. In addition, 485 points or 66.3% of the data are at or below 22 kW, while 558 points or 76.3% are at or below 50 kW. These results indicate that Jakarta's public charging infrastructure is still dominated by lower-power charging stations.

Although most charging stations are concentrated at lower power levels, the presence of higher rated power values, including 100 kW, 120 kW, 180 kW, 200 kW, and 480 kW, creates a right-skewed distribution. This means that the majority of the data are concentrated at lower power levels, particularly 22 kW, while a small number of very high-power chargers form a long tail toward the right side of the distribution.

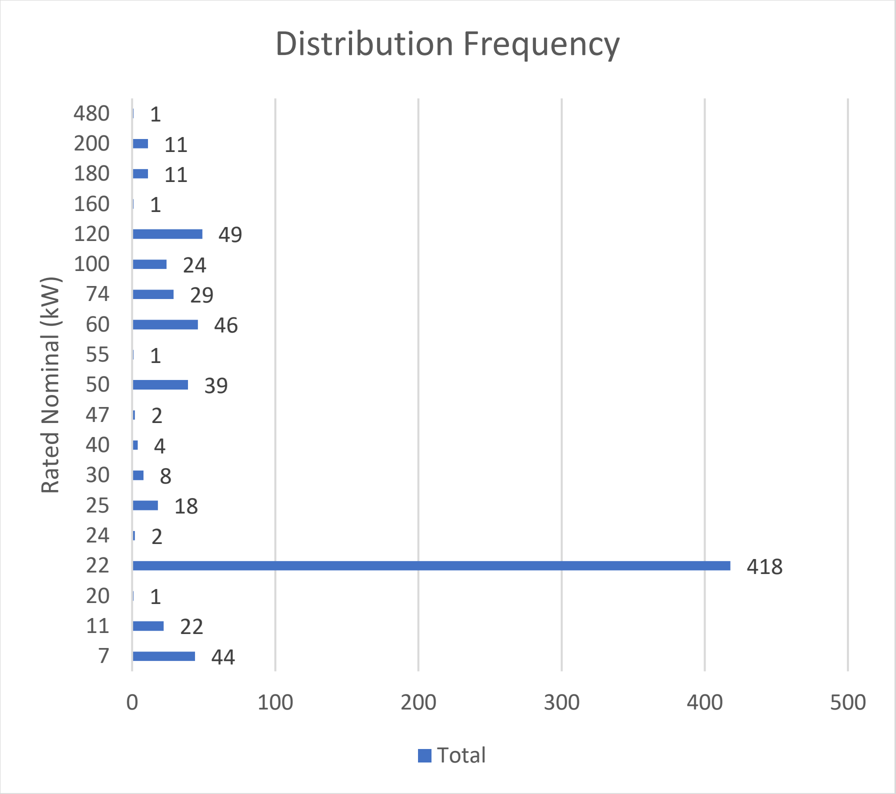

Figure 1 Distribution of public EV charging station rated power in Jakarta
Source: Processed by the authors, 2026.

The distribution pattern suggests that the rated power of public charging stations in Jakarta is not continuously distributed across all power levels. Instead, the data are concentrated at several specific nominal power values. This condition supports the need for a clustering-based approach to identify natural power groups in the dataset.

Determination of the Number of Clusters

The number of clusters was evaluated using the Elbow Method and Silhouette Score. The Elbow Method showed that the reduction in within-cluster sum of squares decreased sharply at lower values of (k), and then began to flatten around (k = 4) to (k = 5). This indicates that adding more clusters beyond this range provides a smaller improvement in cluster compactness.

The Silhouette Score was calculated for (k = 2) to (k = 10). Although the highest Silhouette Score was obtained at (k = 10), this value was not selected as the final number of clusters. The dataset consists of only 19 unique rated power values; therefore, increasing the number of clusters may produce very narrow clusters and lead to over-fragmentation. Such a result may improve the statistical score but reduce the practical usefulness of the classification.

Therefore, (k = 4) was selected as the final number of clusters. This selection was based on three considerations. First, (k = 4) is located within the elbow range. Second, the Silhouette Score at (k = 4) remains high, indicating good cluster separation. Third, four clusters provide practical interpretability and allow direct comparison with the existing four-category charging power classification.

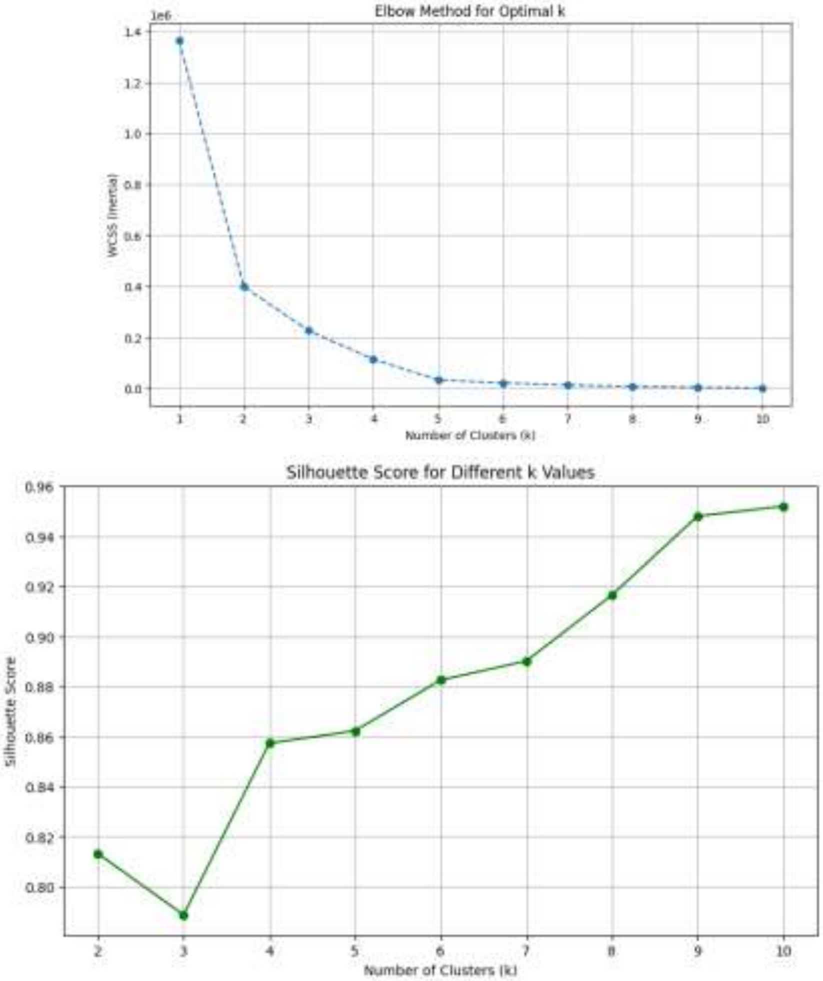

Figure 2 Elbow Method and Silhouette Score for determining the number of clusters

Source: Processed by the authors, 2026.

K-Means Clustering Results

The K-Means Clustering analysis produced four main power clusters: Low Power, Mid Power, High Power, and Ultra High Power. The summary of the clustering results is shown in Table 1.

Table 1 K-Means Clustering Results of Public EV Charging Station Rated Power in Jakarta

Cluster	Power Segment	Power Range (kW)	Centroid (kW)	Number of Points	Proportion
Cluster 1	Low Power	7–40	20.63	517	70.70%
Cluster 2	Mid Power	47–74	59.87	117	16.00%

Cluster 3	High Power	100–120	113.42	73	10.00%
Cluster 4	Ultra-High Power	160–480	200.83	24	3.30%

Source: Processed by the authors, 2026.

The Low Power cluster is the dominant segment, consisting of 517 points or 70.7% of the dataset. This cluster covers the range of 7–40 kW, with a centroid of 20.63 kW. The centroid is close to 22 kW, reflecting the dominance of 22 kW chargers in Jakarta.

The Mid Power cluster consists of 117 points or 16.0% of the dataset. It covers the range of 47–74 kW, with a centroid of 59.87 kW. This cluster represents an intermediate fast-charging segment. The existence of this cluster indicates that chargers around 50–74 kW form a distinct group and should not be directly combined with higher-power chargers in the range of 100 kW and above.

The High Power cluster consists of 73 points or 10.0% of the dataset. It covers the range of 100–120 kW, with a centroid of 113.42 kW. This relatively narrow range indicates a more homogeneous high-power charging segment.

The Ultra High Power cluster consists of 24 points or 3.3% of the dataset. It covers the range of 160–480 kW, with a centroid of 200.83 kW. Although this cluster has the smallest number of points, it represents the emergence of very high-power charging infrastructure in Jakarta.

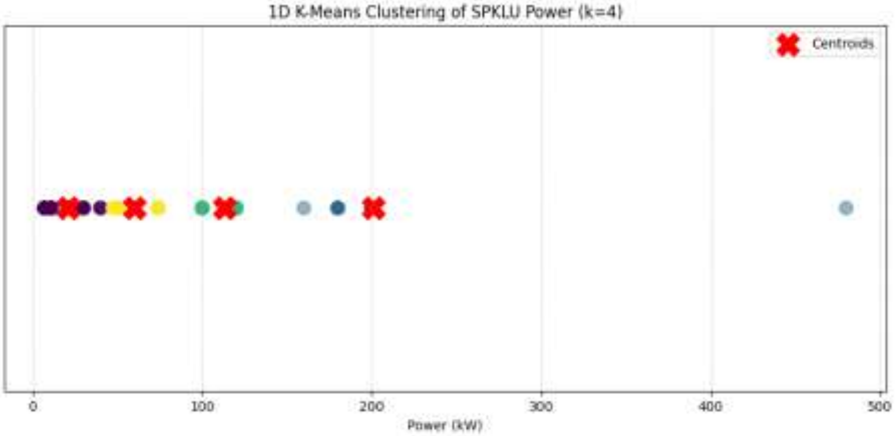

Figure 3 K-Means Clustering result of charging station rated power

Source: Processed by the authors, 2026.

Overall, the clustering results show a pyramid-like structure in Jakarta's public charging infrastructure. Lower-power charging stations dominate the dataset, while higher-power and ultra-high-power charging stations are available in smaller proportions. This pattern suggests that high-power charging infrastructure has started to develop, but the overall infrastructure is still dominated by lower-power charging stations.

Comparison with Existing Power Classification

The clustering results were compared with the existing power classification scheme, which consists of Standard, Medium, Fast, and Ultra Fast charging categories. The existing classification is based on fixed power thresholds. In the dataset, Standard includes 7 kW, Medium includes 11–22 kW, Fast includes 24–50 kW, and Ultra Fast includes all power values above 50 kW.

The comparison shows that the existing classification is simple and easy to apply, but it may oversimplify the actual power distribution, especially in the high-power segment. In the existing classification, chargers rated at 55 kW, 60 kW, 74 kW, 100 kW, 120 kW, 160 kW, 180 kW, 200 kW, and 480 kW are grouped into the same Ultra Fast category. However, the K-Means results show that these power values do not form a single homogeneous group.

The clustering results separate the high-power segment into several more specific groups. Chargers in the range of 47–74 kW are grouped into the Mid Power cluster, chargers in the range of 100–120 kW are grouped into the High Power cluster, and chargers in the range of 160–480 kW are grouped into the Ultra High Power cluster. This indicates that power values above 50 kW have different characteristics and should not necessarily be treated as one uniform category.

Table 2 Comparison between existing power classification and K-Means-based classification

Existing Classification	Power Range / Values	K-Means-Based Interpretation
Standard	7 kW	Included in Low Power
Medium	11–22 kW	Mostly included in Low Power
Fast	24–50 kW	Split between Low Power and Mid Power
Ultra Fast	>50 kW	Split into Mid Power, High Power, and Ultra High Power

Source: Processed by the authors, 2026.

This finding is important because chargers with different rated power levels have different service functions, equipment requirements, grid implications, and potential user segments. For example, a 60-kW charger and a 480-kW charger may both be categorized as Ultra Fast under the existing classification, but they represent very different levels of charging capability. Therefore, a more detailed segmentation can improve the ability of the classification system to represent actual infrastructure development.

Implications for Charging Infrastructure Classification and Planning

The results of this study indicate that data-driven classification can provide a more detailed understanding of public EV charging infrastructure. From a classification perspective, the findings suggest that the category above 50 kW should be evaluated further because the actual data show several distinct power segments rather than one homogeneous group. The proposed K-Means-based classification can serve as an analytical complement to the existing classification scheme.

From an infrastructure planning perspective, the resulting clusters can support more detailed mapping and projection of charging infrastructure development. Instead of only counting the total number of public charging stations, planners can evaluate the composition of charging power segments. This can help identify whether an area is dominated by low-power charging, requires more mid- or high-power charging, or is ready for selective ultra-high-power deployment.

The proposed segmentation may also support the improvement of charging power nomenclature. Low Power can represent the dominant lower-power infrastructure, Mid Power can represent intermediate fast charging, High Power can represent modern high-power charging, and Ultra High Power can represent very high-power charging infrastructure. Such segmentation can help regulators, operators, and infrastructure planners interpret charging station development more accurately.

Although this study focuses on charger rated power classification, the results should also be interpreted in relation to vehicle charging capability. Higher charger power does not always translate into higher charging power received by users, because actual charging power is also limited by vehicle characteristics such as On-Board Charger capacity, DC charging acceptance, battery condition, and charging management strategy. Therefore, future charging infrastructure planning should consider both charger power distribution and the evolving technical characteristics of the EV fleet.

Overall, the findings show that the existing classification remains useful as a simple framework, but it can be strengthened with data-driven segmentation. The K-Means-based classification provides an empirical basis for improving charging station nomenclature, infrastructure mapping, and future charging infrastructure planning in Jakarta and potentially other urban areas with diverse charging power profiles.

CONCLUSION

This study classified the rated power of public electric vehicle charging stations in Jakarta using K-Means Clustering. The analysis was conducted using 731 public charging station points, with rated power as the main clustering variable. The results show that charging station power in Jakarta forms four main clusters: Low Power at 7–40 kW with a centroid of 20.63 kW, Mid Power at 47–74 kW with a centroid of 59.87 kW, High Power at 100–120 kW with a centroid of 113.42 kW, and Ultra High Power at 160–480 kW with a centroid of 200.83 kW. The Low Power cluster is the dominant segment, accounting for 517 points or 70.7% of the total dataset. The comparison with the existing power classification indicates that chargers above 50 kW do not form a homogeneous group. Chargers rated at 60 kW, 120 kW, 200 kW, and 480 kW have different service functions and technical implications, although they may be grouped into the same Ultra Fast category in the existing classification. Therefore, the existing classification can be strengthened through more detailed data-driven segmentation, particularly in the high-power charging segment. Thus, the findings show that K-Means-based classification can provide a more representative understanding of actual charging infrastructure conditions. The proposed classification is not intended to directly replace the existing classification scheme, but to provide an empirical basis for improving charging station nomenclature, infrastructure mapping, and future charging infrastructure planning. Future research can extend this study by incorporating charging transaction data, spatial variables, grid capacity, and alternative clustering methods such as Fuzzy C-Means, DBSCAN, hierarchical clustering, or Gaussian Mixture Model.

REFERENCES

Al-Dahabreh, N., Sayed, M. A., Sarieddine, K., Elhattab, M., Khabbaz, M., Atallah, R., & Assi, C. (2023). A data-driven framework for improving public EV charging infrastructure: Modeling and forecasting. *arXiv*. https://doi.org/10.48550/arXiv.2312.05333

Arooj, A., Ahmed, Q. Z., Farooq, S., Umer, T., Aslam, N., & Alade, T. (2025). Unraveling the smart charging technologies, energy sources, and regulatory standards for EVs. *IEEE Access*.

Author. (2026). *Processed public EV charging station power dataset in Jakarta*.

Deb, S., Tammi, K., Kalita, K., & Mahanta, P. (2018). Review of recent trends in charging infrastructure planning for electric vehicles. *Wiley Interdisciplinary Reviews: Energy and Environment, 7*(6), e306.

Diaz-Londono, C., Zhang, L., De La Cruz, J., Arasteh, H., Tang, D., & Guerrero, J. M. (2026). Quantifying realizable flexibility limits in fast and ultra-fast EV charging using real-world data. *arXiv*. https://doi.org/10.48550/arXiv.2606.29994

Ezugwu, A. E., Abualigah, L., Aremu, A. O. A., & Agushaka, J. O. (2023). K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. *Information Sciences, 622*, 178–210.

Ezugwu, A. E., Ikotun, A. M., Oyelade, O. O., Abualigah, L., Agushaka, J. O., Eke, C. I., & Akinyelu, A. A. (2022). A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges, and future research prospects. *Engineering Applications of Artificial Intelligence, 110*, 104743.

Haces-Fernandez, F. (2023). Risk assessment framework for electric vehicle charging station development in the United States as an ancillary service. *Energies, 16*(24), 8035.

International Energy Agency. (2024). *Global EV outlook 2024: Moving towards increased affordability*. Author.

International Energy Agency. (2025). *Global EV outlook 2025: Expanding electric mobility*. Author.

Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters, 31*(8), 651–666.

Lloyd, S. P. (1982). Least squares quantization in PCM. *IEEE Transactions on Information Theory, 28*(2), 129–137.

MacQueen, J. B. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability* (pp. 281–297). University of California Press.

Mejjaouli, S., Alnourani, S., & Guizani, S. (2026). Optimization methods for electric vehicle charging station placement and vehicle assignment. *Carbon Management, 17*(1), 2654844.

Ministry of Energy and Mineral Resources of the Republic of Indonesia. (2023). *Regulation of the Minister of Energy and Mineral Resources Number 1 of 2023 concerning the provision of electric charging infrastructure for battery-based electric motor vehicles*.

Pandey, A. K., Altamimi, A., Kumar, A., Akhtar, I., & Alam, M. A. (2026). A data-driven approach for EV load modeling and multi-objective approach for integration of EVCS and

DG in distribution systems. *IEEE Access*.

Prakhar, P., Gupta, S., & Jaiswal, R. (2026). Battery technology and charging infrastructure for EVs: A resource-based and dynamic capability view of entrepreneurial opportunities. *Information Discovery and Delivery, 54*(2), 218–235.

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics, 20*, 53–65.

Sadeghi-Barzani, P., Rajabi-Ghahnavieh, A., & Kazemi-Karegar, H. (2014). Optimal fast charging station placing and sizing. *Applied Energy, 125*, 289–299.

Shirvani, R., Bosisio, A., Pomarico, A., Berizzi, A., Mosca, C., Cuccia, P., & Tisti, P. (2025). A data-driven approach for clustering extra high voltage buses: A case study on the Italian transmission network. *Sustainable Energy, Grids and Networks*, 101847.

Sun, S., Li, N., Zhang, L., Zhao, D., Lun, D., & Feng, L. (2025). Integrated data-driven topology reconstruction and risk-aware reconfiguration for resilient power distribution systems under incomplete observability. *Scientific Reports, 15*(1), 30661.

Wady, A. F., & Consoni, F. L. (2025). Regulatory sandbox for electric mobility: Enhancing charging infrastructure and innovation. *Renewable and Sustainable Energy Reviews, 213*, 115496.

Yuan, H., Ma, M., Zhou, N., Deng, Y., Liu,J., Zhang, S., & Ma, Z. (2025). Planning for future EV charging infrastructure: A city-scale assessment of demand and capacity. *arXiv*. https://doi.org/10.48550/arXiv.2508.16175