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Evaluating clustering algorithms with integrated electric vehicle chargers for demand-side management

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ABSTRACT

The integration of electric vehicles (EVs) and their effects on power grids pose several challenges for distribution operators. These challenges are due to uncertain and difficult-to-predict loads. Every electric vehicle charger (EVC) has its specific pattern. This challenge can be addressed by clustering methods to determine EVC energy consumption clusters. Demand side management (DSM) is an effective solution to manage the incoming load of EVs and the large number of EVCs. Considering the challenges of peak consumptions and valleys, the adoption of vehicle-to-grid (V2G) technology requires mastering load clusters to develop energy management systems for distributors. This work used clustering algorithms (K-means, DBSCAN, C-means, BIRCH, Mean-Shift, OPTICS) to identify load curve patterns, and for performance evaluation of algorithms, it worked on metrics like the Silhouette coefficient, Calinski-Harabasz index (CHI), and Davies-Bouldin index (DBI) to evaluate results. C-means achieves the best overall clustering performance, evidenced by the highest Silhouette coefficient (0.30) and a strong Calinski-Harabasz score (543). Mean-Shift excels in the Davies-Bouldin Index (1.13) but underperforms on other metrics. BIRCH provides a balanced approach, delivering moderate results across evaluated metrics.

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1. INTRODUCTION

Considering climate change and the associated threats of global warming, and the dangers of greenhouse gas emissions on the planet, the reduction of reducing greenhouse gas (GHG) and the decarbonization of road transportation are considered an important step toward preserving the environment. To achieve this, governments are encouraging the use of electric vehicles and hybrid electric vehicles by offering tax incentives to consumers and replacing government fleets with electric vehicles (EVs) and hybrid electric vehicles (HEVs) [1]. These measures include tax incentives for consumers and initiatives to replace government fleets with EVs and HEVs, aiming to decrease the carbon footprint of transportation and mitigate the environmental impacts of fossil fuels. On one hand, it remains an effective solution for global warming, but on the other hand, electricity distribution grids are not yet prepared for the mass integration of large fleets of electric vehicles. For electricity distribution grids, it is a difficult challenge to receive and provide enough unplanned power to a huge number of electric vehicles through electric vehicle chargers.

Demand side management (DSM) is the planning, implementation, and monitoring of electrical grid utility activities to effectively influence customer use of electricity in ways that will produce desired changes in the load shape [2]. Its main goal is to ameliorate efficiency of the electrical grid by implementing strategies to minimize energy consumption during peak demand periods and encourage energy conservation. By effectively managing the demand for electricity, DSM helps to minimize losses in the electrical power system and enhance its overall efficiency [3], [4]. And clustering is a methodology inside unsupervised learning that categorizes data into multiple groups according to specific criteria. It aids users in comprehending the patterns and groupings within a dataset [5]. Clustering technique can be used to identify patterns, similarities, or differences among curves, which can be helpful for various purposes such as energy consumption, market analysis, customer segmentation, or targeted marketing strategies [5]. Having a comprehensive understanding of clustering algorithms allows engineers to gain a nuanced perspective on their capabilities, helping them choose the most appropriate approach for various applications [6]. Clustering results offer benefits for energy providers by enabling effective customer segmentation, which allows for tailored marketing and personalized services. It enhances demand forecasting, helping providers optimize energy distribution. Clustering also aids in load management by identifying similar customer load profiles, facilitating demand response programs that lower peak demand and operational costs. EVC planning benefits from clustering insights by pinpointing areas with specific needs, ensuring strategic investment and resource allocation.

Numerous studies have explored various facets of EVs using clustering techniques to simplify network computational complexity during analysis. Key focus areas in existing research include modeling EV user behavior [7], EV driving cycles [8], used EV batteries [9], clustering [10], and EV charging stations [11]. Nevertheless, additional EV aspects require deeper investigation through clustering methods. These include analyzing the effects of EVs on different distribution circuits [12], examining charging infrastructure in emergency situations [13], exploring equity issues in rebate distributions [14], and employing big data in cluster analysis to enhance transportation network management [15]. In [16], authors show that K-means exceeds the performance of other algorithms, like DBSCAN, K-Medoids, Agglomerative clustering, and Gaussian mixture models (GMM), by achieving a Calinski-Harabasz index (CHI) of 1200, a Silhouette score of 0.45, and a Davies-Bouldin index (DBI) reached 0.74. Using the same methodology, Hasan *et al.* [17] worked on clustering algorithms K-means, Hierarchical clustering, and DBSCAN for determining the load pattern of daily and weekly EV charging profile clusters. In this work authors tried to select the optimum number of clusters, so they found that both K-means and hierarchical methods feature two major clusters containing between 30 and 40% of customers and two smaller clusters with 10 to 20% of customers. Conversely, DBSCAN presents one major cluster (in daily profile) comprising approximately 70% of customers. And for the analysis of the effect of corona virus on EV charging patterns, Shahriar and Al-Ali [18] explored the clustering using the same metrics (Silhouette score, DBI, and CHI) to evaluate K-means, Hierarchical clustering, and GMM results. In this work K-means reveals the highest Silouhette score, and also the highest CHI. In the other side, Richard *et al.* [19] proposed a clustering process (multiple temporal granularities) which serves for the creation of relative rankings of similar clustering results over multiple weeks.

In this work, the authors focused on EV load curve clustering and the extraction of EV users' power consumption patterns by using clustering algorithms. Starting by introducing electric vehicle clusters, the authors provide information about clustering techniques, algorithms used, and metrics. For electricity distributors, it is imperative to master the power demand curve of every charging station to have a clear understanding of its pattern (peak load, valley load), which is why the load curves clusters of every charging station are analyzed. The project involves gathering data and extracting load curves, clusters, and metrics to understand the behavior of electric vehicle chargers over various time units (hour, day, month, year). It is based on the principle of managing energy consumption. In the context of electric and hybrid electric mobility, the anticipated future integration of electric vehicles, coupled with the widespread addition of numerous charging stations into distribution grids, is expected to significantly impact electrical energy consumption and subsequently, the energy distribution infrastructure. The results showed that C-means surpasses other methods in key metrics, achieving the highest metric scores. This indicates that C-means is superior at creating clear and distinct groupings. Although Mean-Shift has the lowest DBI, suggesting less cluster similarity, its lower scores in the Silhouette coefficient and CHI suggest it may not be as adept at creating well-defined, separate clusters. As a contribution of this paper to the existing literature, the paper proposes to exploit these load curve patterns for DSM to solve the challenge of mass integration of EVC and the problems of load management (peak shaving, valley filling, efficient use of renewable energy sources).

2. METHOD

The experimental procedure was conducted in five sequential stages to ensure full reproducibility of the clustering of EV charging profiles.

a. Data collection and acquisition: EV charging data were gathered from a CS 2018 to 2023. The dataset of 6,282 charging session, in CSV format, includes key variables such as the start time of charging, instantaneous charging power, and total energy consumption per session. Monitoring equipment was calibrated to ensure synchronization and accuracy.
b. Data cleaning and preprocessing: The raw dataset was imported into Python using libraries like Pandas. Erroneous entries, missing values, and periods of inactivity (due to equipment failures, power outage) were systematically removed or replaced with zeros to ensure data integrity.
c. Feature extraction and transformation: The cleaned data were processed to extract critical features such as the charging session start time, the time-series of charging power, session duration. These features were normalized to prevent scale imbalances during clustering.
d. Clustering analysis: Clustering algorithms were applied to the processed dataset to assign each EV charging profile to distinct groups. Standard algorithms (K-means, OPTICS, C-means, DBSCAN, BIRCH, Mean-Shift) were used to capture both hard and soft clustering characteristics. Parameters for each algorithm (like the number of clusters for K-means) were initially determined by exploratory analysis and refined through iterative runs until convergence.
e. Evaluation and analysis: The quality and stability of the resulting clusters were assessed using internal validation metrics such as the Silhouette coefficient, CHI, and DBI, providing quantitative justification for the selected methods. The distinct clusters reveal varying charging patterns and peak usage times, offering insights into power demand and grid stability, and supporting tailored load management and personalized marketing strategies.

Figure 1 presents proposed paper's methodology for clustering EVC profiles. All stages were implemented in Python using standard libraries (Pandas, NumPy, Scikit-learn), and detailed experimental parameters and code are provided to ensure that the methodology can be exactly replicated by other researchers.

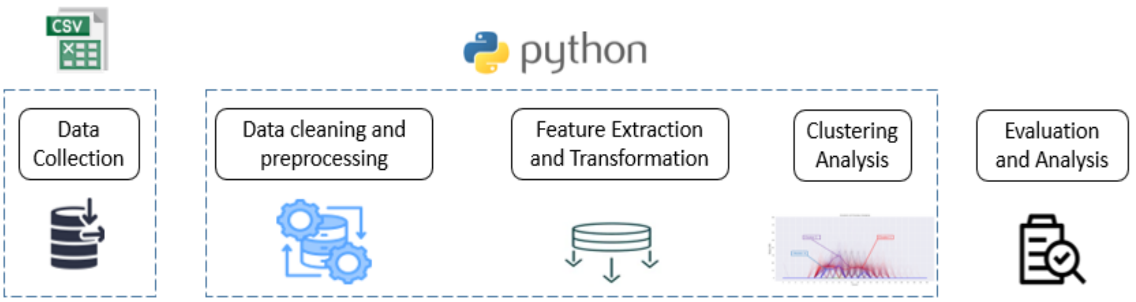

Figure 1. Proposed methodology for clustering EVC profiles

2.1. Clustering algorithms

The K-means algorithm is widely used for partitioning data in various applications. However, it has some limitations, such as the difficulty in determining the actual number of clusters and selecting initial cluster centroids. To address these issues, extensive research has been conducted in this field, resulting in several modifications to the K-means algorithm. In order to enhance the algorithm and overcome its challenges, it is important to review the existing works and research initiatives in this area. In the following discussion, we will explore the major advancements and improvements made in this field [20].

Density-based spatial clustering of applications with noise algorithm DBSCAN is an algorithm that detect clusters of various shapes. It identifies clusters by analyzing the density of points, with high point density indicating the presence of clusters. This algorithm is particularly useful for handling large datasets that contain noise. Additionally, it is capable of distinguishing clusters of different sizes and shapes [21]. This algorithm is especially useful for handling large datasets with noise. It can also distinguish between clusters of different sizes and shapes. The essential concept of the DBSCAN is that, in a cluster, for each point the neighborhood of a specific radius should have a minimum number of points, the density in the neighborhood must surpass a set threshold [22], [23].

C-means algorithm is one of the unsupervised clustering algorithms that allows a single data point to belong to multiple clusters. It can be used for various feature analysis, clustering, and classifier construction tasks. C-means has been widely applied in different fields. Unlike K-means, C-means assigns each pattern a degree of membership to a cluster, resulting in a fuzzy clustering [5].

Balanced iterative reducing and clustering using hierarchies (BIRCH) is an agglomerative hierarchical clustering algorithm developed for efficiently clustering large volumes of metric data. It is particularly well-suited for scenarios with limited main memory and is capable of operating in linear time with just a single scan of the database. BIRCH introduces the concepts of clustering feature and clustering feature tree, which serve to compactly summarize and represent clusters [24]. BIRCH utilizes an integrated hierarchical approach by employing cluster features and a cluster feature tree. The cluster feature tree efficiently summarizes clustering information while using significantly less memory than the original dataset. As a result, BIRCH enhances the performance of clustering large datasets, offering both high speed and scalability [25].

Mean-Shift clustering is a non-parametric, density-based algorithm designed to identify clusters within a dataset. It is particularly effective for datasets containing clusters of arbitrary shapes that are not easily separated by linear boundaries. The core idea of Mean-Shift is to iteratively move each data point toward the mode, or the region of highest data density, within a specified radius. This process continues until the points converge to local maxima of the density function, which correspond to the clusters present in the data.

Ordering points to identify the clustering structure (OPTICS) is a density-based clustering algorithm designed for spatial data. While similar to DBSCAN, OPTICS overcomes DBSCAN's limitation in detecting clusters of varying densities. It achieves this by linearly ordering the data points so that spatially closest points are neighbors in the sequence. For each point, OPTICS records a specific distance value that indicates the minimum density required for both the point and its predecessor to be considered part of the same cluster.

2.2. Evaluation metrics

The silhouette coefficient_metric measures how well each data point fits within its own cluster compared to other clusters. It ranges from -1 to 1. where values close to 1 indicate well-separated clusters. Values close to 0 indicate overlapping clusters. Negative values suggest that data points may have been assigned to the wrong cluster [26].

The Calinski-Harabasz index, is a measure used to evaluate the quality of a data partition in clustering. It is calculated by comparing the dispersion between clusters with the dispersion within clusters. A higher Calinski-Harabasz index indicates a more coherent and distinct data partition. Also known as the variance ratio criterion, this metric quantifies the ratio of between-cluster variance to within-cluster variance. Higher values indicate more compact and well-separated clusters [26].

The Davies-Bouldin index metric calculates the average similarity between each cluster and its most similar cluster. Taking into account both the within-cluster and between-cluster distances. Lower values indicate more compact and well-separated clusters. The Davies-Bouldin index is based on the approximately estimation of the distances between clusters and their dispersions to obtain a final value that represents the quality of the partition [27].

3. RESULTS AND DISCUSSION

Table 1 displays the outcomes derived from the clustering algorithms. Figure 1 on the other hand, visually represents these results in the form of a curve. The curves are providing a graphical interpretation of the data presented in Table 1.

Table 1. Metrics comparison of clustering algorithms

Variable	K-means	C-means	DBSCAN	BIRCH	OPTICS	Mean-Shift
Silhouette coefficient	0.23	0.30	0.25	0.25	0.25	0.13
Davies-Bouldin index	1.94	1.92	2.56	1.40	2.44	1.13
Calinski-Harabasz score	407	543	229	106	232	101

As Table 1 reveal, the Silhouette coefficient metric ranges from -1 to 1, with 1 indicating that the clusters are well apart from each other and -1 indicating that the clusters are too close to each other. Higher values are better. According to this metric, C-means performs the best with a score of 0.30, while Mean-Shift performs the worst with a score of 0.13. For DBI, it indicates the average similarity between clusters, where similarity is a measure that compares the distance between clusters with the size of the clusters themselves. Lower values are better. According to this metric, Mean-Shift performs the best with a score of 1.13, while DBSCAN has the worst score of 2.56. CHI: This score is used to evaluate the model where higher is better. It calculates the ratio of the sum of between-cluster dispersion and of inter-cluster dispersion for all clusters. According to this metric, C-means performs the best with a score of 543, while Mean-Shift has the lowest score of 101.

Overall, it appears that C-means performs the best when considering all three metrics. It has the highest silhouette coefficient and CHI, indicating well-separated clusters and a good degree of separation between them. Meanwhile, Mean-Shift has the lowest DBI, indicating less similarity between clusters, but its low Silhouette coefficient and CHI suggest that it may not be as effective at creating distinct, well-separated clusters. Therefore, considering these metrics, C-means seems to be the most efficient clustering algorithm.

– K-means: Figure 2 illustrates the clustering results using the K-means algorithm into three distinct clusters. Cluster 1 shows moderate to high energy consumption with a peak in the late morning (around 10 a.m.), likely representing users who charge after commuting to work. Clusters 1, 2, and 3 are distinct from each other, which indicates that K-means successfully captured different user behaviors.

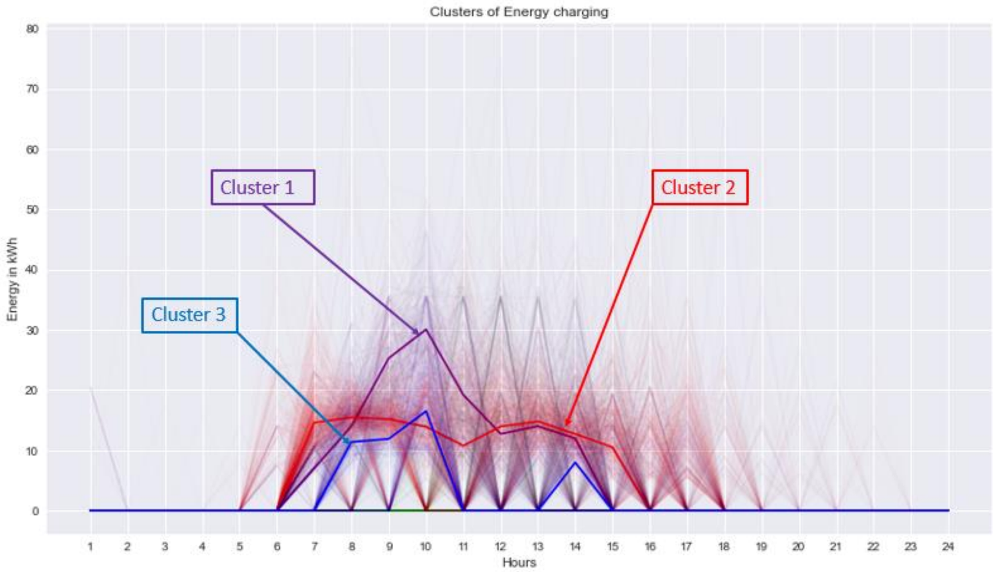

Figure 2. Clusters of energy charging using K-means algorithm

– C-means: Figure 3 represents three clusters. It is clear that clusters 2 and 3 are similar, showing moderate to high energy consumption during the morning and afternoon with a break at midday during the lunch period. For all of these clusters, from 6 p.m. to approximately 6 a.m., the consumption is null.

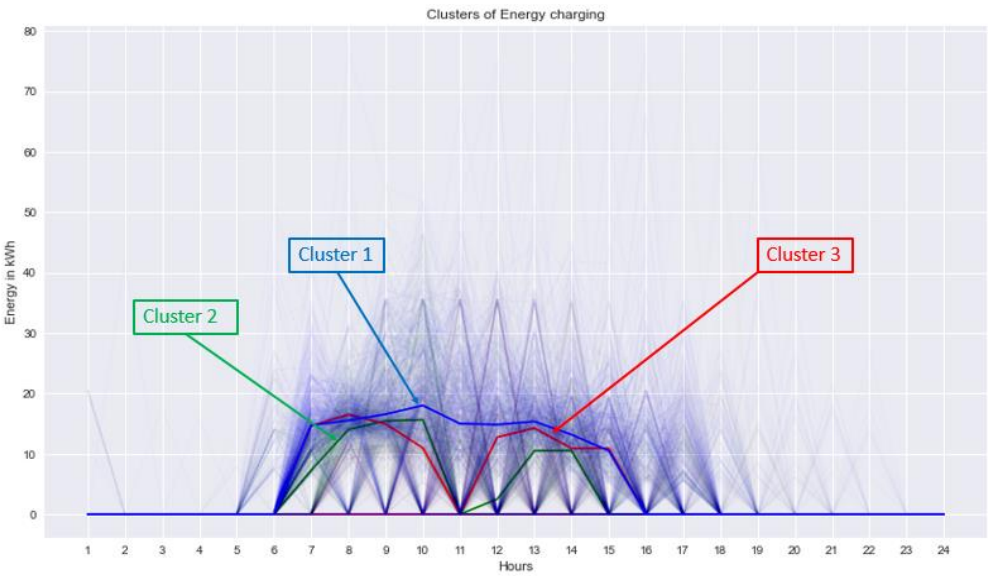

Figure 3. Clusters of energy charging using C-means algorithm

– DBSCAN: For the results of DBSCAN algorithm are shown in Figure 4. The results show two clusters so different from each other's. Cluster 1 reveals moderate energy consumption generally with a small peak in the late morning.

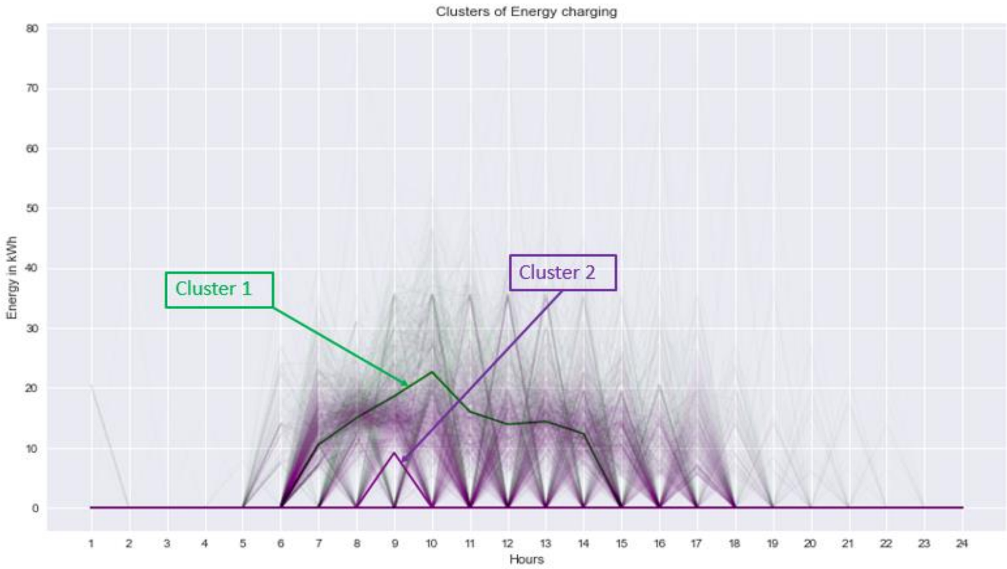

Figure 4. Clusters of energy charging using DBSCAN algorithm

– BIRCH: Clustering results for the BIRCH algorithm represent four clusters, as shown in Figure 5. Cluster 1 shows a huge peak in consumption just before midday. Cluster 2 reveals three consumption peaks in the morning, midday, and at the end of the afternoon, which correspond to high traffic density periods.

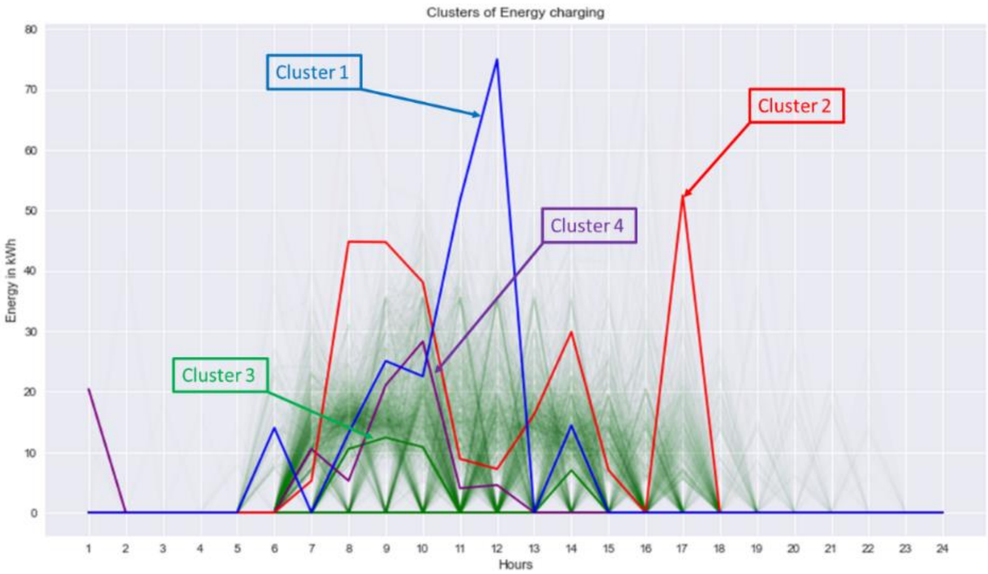

Figure 5. Clusters of energy charging using BIRCH algorithm

– OPTICS: OPTICS algorithm gives consumption patterns somewhat similar to DBSCAN. Figure 6 reveals four clusters in which three clusters are very similar (clusters 2, 3, and 4), with low energy consumption throughout the day except for the period between 10 a.m. and 12 p.m. Cluster 1 represents normal energy consumption during the day with inactivity from the end of the day to the start of the next day.

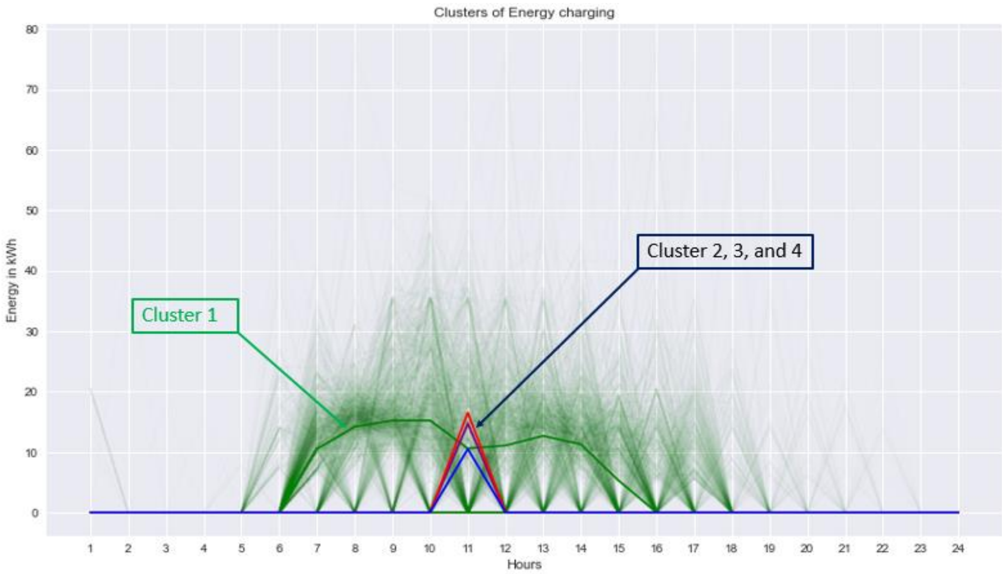

Figure 6. Clusters of energy charging using OPTICS algorithm

- Mean-Shift: Mean-Shift algorithm's result is shown in Figure 7. Clusters 1 and 3 reveal normal and continuous consumption during the day from 6 a.m. to 6 p.m. Cluster 2 shows activity at the start of the day and at the end of the day, and Cluster 4 illustrates moderate consumption at the start of the day and inactivity outside this period.

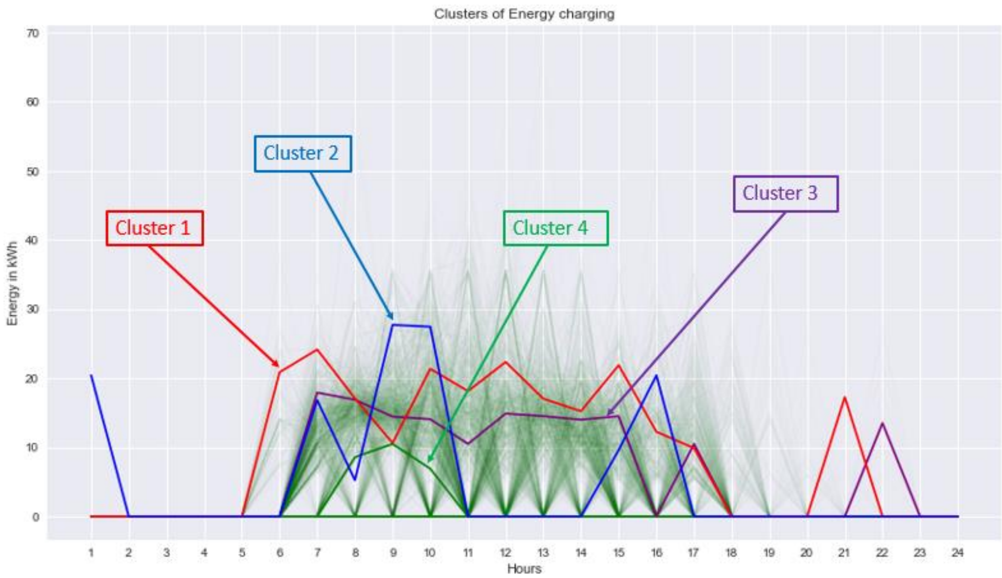

Figure 7. Clusters of energy charging using Mean-Shift algorithm

In comparison with other works, in [16], K-means outperforms the other algorithms with the best metrics results, achieving a CHI of 1,200, a silhouette score 0.45, and DBI of 0.74. K-Medoid and Agglomerative clustering also reveal good and approximately equal results. In this work, DBSCAN algorithms have the lowest results, because of its lowest CHI and silhouette score, and the highest DBI of 1.78. K-means also outperforms the other algorithms in [18], Hierarchical clustering algorithm reveals also good results with 0.38 in silhouette score and 0.74 in DBI, and 2,270 for the CHI. GMM in this research paper gives the lowest results which made this algorithm far from K-means and Hierarchical clustering algorithm.

4. CONCLUSION AND PERSPECTIVE

The advent of electric vehicles presents significant challenges for power grid distribution and production operators due to the unpredictable load. These challenges stem from the unique characteristics of each electric vehicle charger, including location and energy consumption. Clustering methods will help identify patterns in energy consumption, serving to manage the increasing electrical load from electric vehicle users and chargers.

This study evaluates the effectiveness of clustering algorithms, including K-means, DBSCAN, C-means, BIRCH, Mean-Shift, and OPTICS, using performance metrics such as the Silhouette coefficient, CHI, and DBI. The results differ in terms of load curve clusters, cluster numbers, peak values, and metrics. Based on the clustering performance metrics, C-means demonstrates the best overall performance with the highest Silhouette coefficient (0.30) and a strong Calinski-Harabasz score (543), while Mean-Shift shows the best Davies-Bouldin index (1.13) but performs poorly on other metrics. BIRCH offers a balanced performance with moderate scores across all metrics. The results suggest that C-means is the most suitable algorithm for clustering EV charging profiles, providing the best balance between cluster separation and cohesion. By mastering these load clusters, operators can better adopt vehicle-to-grid (V2G) technology and develop more efficient energy management systems, mitigating the impact of peak consumption and valleys. Building upon these findings, we identify a significant gap in the field, particularly concerning the effective integration of EV charger patterns and other inputs to enhance the management of EVC power demand. The development of protocols for data exchange between EVs, EVCs, and central system management is a critical aspect that needs to be addressed. The central system, tasked with the management of electric vehicle chargers, could greatly benefit from such advancements.

In light of this, our perspectives aim to explore the development of V2G protocols. The development will be through implementing and intelligent energy management algorithms within a centralized smart charging management system. This development will enable the enhancing grid stability and optimal energy distribution.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, AA. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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