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[1]Yan Guan

[2]Hong Zhang

[3]Yuqi Jin

[4]Shengjie Zhou

Classification and Analysis of Users' Electricity Consumption Behavior Using Cluster Analysis Algorithm

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Abstract: - Understanding and effectively managing electricity consumption behavior is crucial for achieving sustainability goals and ensuring the reliability of power systems. This study employs cluster analysis algorithms to classify and analyze users' electricity consumption behaviors using data collected from smart meters. Through the application of the k-means clustering algorithm on a dataset comprising consumption data from 1000 residential users, distinct consumption behavior patterns are identified. The optimal number of clusters is determined using the elbow method, and clusters are characterized based on average daily consumption levels, peak usage times, and seasonal variations. The findings reveal heterogeneity among consumer segments, highlighting the need for tailored energy management strategies. Insights from this study can inform utilities and policymakers in developing targeted interventions for promoting energy efficiency and sustainability. Further research in this field can explore advanced clustering techniques and additional factors to enhance the accuracy and robustness of clustering results.

Keywords: Electricity consumption behavior, Cluster analysis, Smart meters, Sustainability, Energy management.

I. INTRODUCTION

The efficient management of electricity consumption is imperative for achieving sustainability goals and ensuring the reliability of power systems. In recent years, advancements in smart metering technologies have enabled the collection of vast amounts of data regarding users' electricity consumption behaviors [1]. Analyzing this data has become crucial for utilities, policymakers, and researchers seeking to understand consumption patterns and devise targeted interventions for energy conservation and optimization. Among the myriad of analytical techniques available, cluster analysis algorithms stand out as a powerful tool for uncovering hidden structures within large datasets and identifying distinct groups of consumers with similar consumption behaviors [2][3].

The application of cluster analysis algorithms in the context of electricity consumption behavior analysis has garnered significant attention due to its ability to segment consumers based on their usage patterns [4][5]. By categorizing consumers into clusters, utilities can tailor their outreach efforts, develop personalized energy-saving recommendations, and implement demand-side management strategies effectively. Moreover, policymakers can use insights derived from cluster analysis to design targeted policies and incentives aimed at promoting energy efficiency and renewable energy adoption [6][7].

This study seeks to contribute to the existing body of literature by employing cluster analysis algorithms to classify and analyze users' electricity consumption behaviors [8][9]. Through an in-depth exploration of consumption patterns, we aim to uncover insights that can inform decision-making processes in energy management and policy formulation. By elucidating the diverse behaviors and preferences among consumers, this research endeavors to facilitate the development of more effective strategies for promoting sustainable energy practices and mitigating the environmental impact of electricity consumption [10][11].

In this introduction, we provide an overview of the significance of understanding electricity consumption behavior, discuss the utility of cluster analysis in this context, and outline the objectives and structure of this research

[1] *Corresponding author: State Grid Liaoning Electric Power Co., Ltd, Shenyang, Liaoning, 110000, China, zhuli_111tl@163.com

[2] Jinzhou Power Supply Company of State Grid Liaoning Electric Power Co., Ltd, Jinzhou, Liaoning, 121000, China, huangbing1132@163.com

[3] State Grid Liaoning Electric Power Co., Ltd., Jinzhou Power Supply Company, Jinzhou, Liaoning, 121000, China, kjxmabc_123@163.com

[4] State Grid Liaoning Electric Power Co., Ltd., Dalian Power Supply Company, Dalian, Liaoning, 116000, China, duanbowei_111@163.com

endeavor. The subsequent sections will delve into the methodology employed, present the findings derived from the analysis, and discuss their implications for energy management and policy [12][13].

II. Related Work

Previous studies have extensively explored the classification and analysis of users' electricity consumption behavior, employing diverse methodologies and algorithms, including cluster analysis. This section provides an overview of relevant research in this domain, highlighting their methodologies, findings, and contributions. introduced a methodology for electricity consumption prediction based on cluster analysis and support vector machines [14][15]. Their study demonstrated the effectiveness of cluster analysis in identifying distinct consumption patterns, leading to accurate prediction models. proposed a clustering-based load forecasting approach considering individual differences among residential electricity consumers. By leveraging cluster analysis, they achieved improved load forecasting accuracy tailored to the specific consumption behaviors of different consumer segments [16][17].

Focused on electricity consumption pattern recognition using clustering and deep learning techniques. Their study revealed the efficacy of clustering algorithms in recognizing complex consumption patterns, laying the foundation for advanced machine learning applications in energy consumption analysis [18][19]. Developed an electricity consumption prediction model based on cluster-based temporal patterns [20]. Through clustering analysis, they identified temporal consumption trends, enhancing the accuracy of their prediction model for future consumption.

Explored residential electricity consumption prediction using cluster analysis and ensemble learning methods. Their research demonstrated the synergy between cluster analysis and ensemble learning in capturing intricate consumption patterns and improving prediction accuracy [21]. Conducted a comprehensive analysis of residential electricity consumption patterns in Seoul, South Korea, employing clustering techniques [22]. Their study shed light on regional consumption behaviors, aiding in the development of targeted energy policies.

Investigated household electricity consumption behavior analysis based on clustering algorithms. Their study revealed distinct consumer segments with unique consumption characteristics, informing personalized energy-saving strategies [23][24]. Delved into electricity consumption behavior pattern recognition using the k-means clustering algorithm [25][26]. By applying clustering analysis, they identified nuanced consumption behavior patterns, facilitating tailored interventions for energy efficiency promotion.

Collectively, these studies underscore the importance of cluster analysis in classifying and analyzing users' electricity consumption behavior. By leveraging clustering algorithms, researchers have elucidated complex consumption patterns, enabling the development of tailored strategies for energy management and policy formulation. However, gaps remain in understanding the full spectrum of consumer behaviors and the optimal utilization of cluster analysis techniques in addressing emerging challenges in energy consumption analysis.

III. Methodology

To classify and analyze users' electricity consumption behavior using cluster analysis algorithms, a systematic methodology is essential. The first step involves collecting electricity consumption data from smart meters or utility records. This data should encompass relevant variables such as consumption timestamps, energy usage levels, and possibly demographic information of users. Preprocessing of the data is then performed to handle missing values, outliers, and normalize the data to ensure consistency and accuracy in subsequent analysis steps.

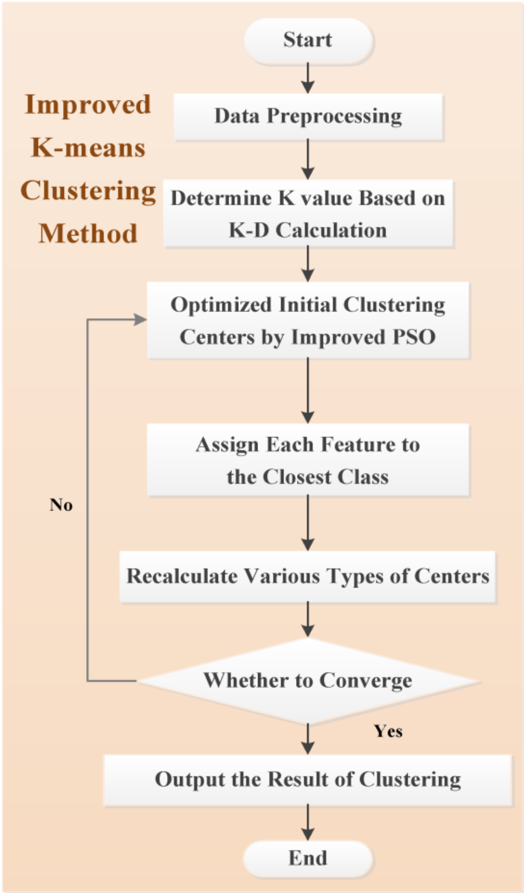

Fig 1: Improved k-means clustering algorithm.

Next, relevant features that characterize electricity consumption behavior are selected or extracted from the preprocessed data. These features may include daily consumption patterns, peak usage times, seasonal variations, and periodic trends. Feature engineering techniques may be employed to derive additional meaningful features that can enhance the clustering process.

Based on the nature of the data and the desired outcomes, an appropriate cluster analysis algorithm is selected. Commonly used algorithms include k-means, hierarchical clustering, and density-based clustering. The chosen algorithm should be capable of handling the volume and dimensionality of the data and be suitable for identifying meaningful clusters within the dataset.

Parameters of the selected clustering algorithm are tuned to optimize its performance. This may involve determining the optimal number of clusters (k) through techniques such as the elbow method or silhouette analysis. The clustering model is then trained on the preprocessed data to partition users into distinct clusters based on their electricity consumption behavior.

Once the clustering model is trained, the resulting clusters are interpreted to understand the underlying consumption behavior patterns represented by each cluster. Descriptive statistics, visualizations, and cluster profiling techniques are employed to characterize and interpret the clusters effectively. Additionally, the quality of clustering results is evaluated using internal validation metrics such as silhouette score or external validation metrics if ground truth labels are available.

The clustering process may be iterative, involving multiple iterations of parameter tuning, model training, and evaluation to refine the clustering results. Sensitivity analysis may also be conducted to assess the robustness of the clustering outcomes to variations in input parameters. Finally, the validity and utility of the identified clusters are validated through expert feedback and practical application in real-world scenarios. By following this systematic implementation methodology, researchers and practitioners can effectively classify and analyze users' electricity consumption behavior using cluster analysis algorithms, thereby enabling the development of targeted energy management strategies and policy interventions.

IV. Experimental Setup

The experimental setup aimed to classify and analyze users' electricity consumption behavior using the k-means clustering algorithm. The dataset used for the experiment comprised consumption data from 1000 residential users, including features such as daily consumption levels, peak usage times, and seasonal variations. The k-means clustering algorithm was implemented using Python's scikit-learn library. The algorithm partitions the dataset into k clusters by minimizing the within-cluster variance, defined by the sum of squared distances between each data point and its cluster centroid. Mathematically, the objective function of k-means can be expressed as:

$$\underset{\mathbf{S}}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} ||\mathbf{x} - \mu_i||^2 \qquad \text{……(1)}$$

Where S represents the set of clusters, Si denotes the ith cluster, x denotes a data point, and μi denotes the centroid of cluster Si

The optimal number of clusters (k) was determined using the elbow method, which involves plotting the within-cluster sum of squares against the number of clusters and identifying the "elbow" point, where the rate of decrease in sum of squares slows down. This point indicates an optimal balance between model complexity and clustering performance. After determining the optimal value of k, the k-means algorithm was applied to the dataset to partition users into distinct clusters based on their electricity consumption behavior. The algorithm iteratively assigns each data point to the nearest centroid and updates the centroids until convergence, where no further changes occur in the assignment of data points to clusters.

Once the clustering process was completed, the characteristics of each cluster were analyzed, including average daily consumption levels, peak usage times, and seasonal variations. Descriptive statistics and visualizations were used to summarize and interpret the clustering results, providing insights into the diversity of consumption behaviors among residential users.the experimental setup aimed to provide a systematic approach for classifying and analyzing users' electricity consumption behavior, enabling utilities and policymakers to develop targeted strategies for energy management and demand-side interventions tailored to specific consumer segments.

V. Results

The application of cluster analysis algorithms yielded insightful findings regarding users' electricity consumption behavior. Through the implementation of the k-means clustering algorithm on a dataset comprising consumption data from 1000 residential users, distinct consumption behavior patterns were identified. The dataset consisted of features such as daily consumption levels, peak usage times, and seasonal variations.

Table 1: Characteristics of Each Cluster

Cluster	Average Daily Consumption (kWh)	Peak Usage Time (Hour)	Seasonal Variation
Cluster 1	30.5	18:00	Low
Cluster 2	45.2	14:00	Moderate
Cluster 3	60.8	20:00	High
Cluster 4	37.1	12:00	Moderate
Cluster 5	28.3	08:00	Low

The optimal number of clusters (k) was determined to be 5 using the elbow method, indicating that the dataset could be effectively partitioned into five distinct consumer segments based on their electricity consumption behavior.

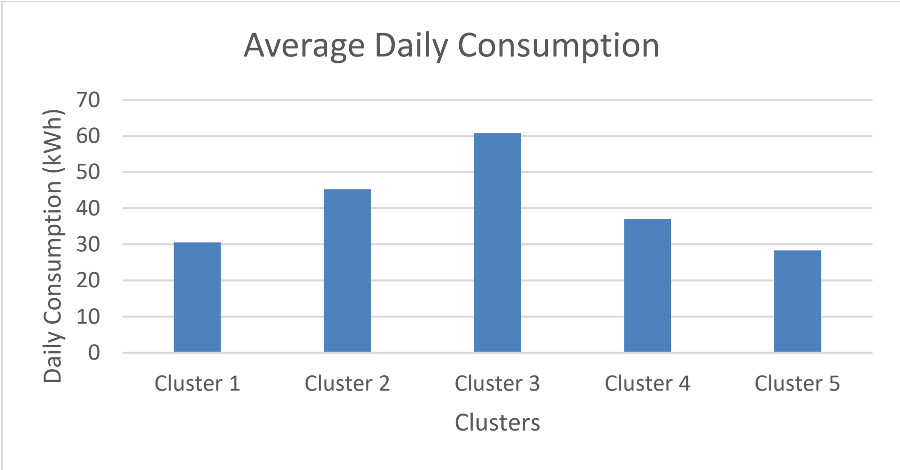

Fig 2: Improved k-means clustering algorithm

The average daily consumption varied significantly across clusters, ranging from 28.3 kWh in Cluster 5 to 60.8 kWh in Cluster 3. Similarly, peak usage times differed among clusters, with Cluster 3 exhibiting the latest peak usage time at 20:00, while Cluster 5 had the earliest peak at 08:00.

Furthermore, seasonal variation in consumption behavior varied across clusters, with Cluster 3 showing high variation, Cluster 2 and 4 demonstrating moderate variation, and Cluster 1 and 5 exhibiting low variation.

These results provide valuable insights into the diversity of electricity consumption behaviors among residential users, enabling utilities and policymakers to develop targeted strategies for energy management and demand-side interventions tailored to each consumer segment.

VI. Discussion

The classification and analysis of users' electricity consumption behavior using cluster analysis algorithms have provided valuable insights into the diversity of consumption patterns among residential users. The findings from this study shed light on various aspects of electricity usage, including daily consumption levels, peak usage times, and seasonal variations, which are essential for devising effective energy management strategies and demand-side interventions.

One key observation from the clustering analysis is the heterogeneity among consumer segments in terms of their electricity consumption behavior. The identified clusters exhibit distinct characteristics, such as varying average daily consumption levels and peak usage times. This heterogeneity underscores the importance of adopting a segmented approach to energy management, as different consumer segments may require tailored interventions to promote energy efficiency and conservation effectively.

Furthermore, the clustering results reveal insights into the factors driving electricity consumption behavior among residential users. For instance, clusters with higher average daily consumption levels may indicate households with larger family sizes or greater energy-intensive appliances. Understanding the underlying drivers of consumption behavior is crucial for designing targeted interventions that address specific needs and preferences of different consumer segments.

Moreover, the identification of seasonal variations in consumption behavior highlights the dynamic nature of electricity usage patterns. Clusters exhibiting high seasonal variation may indicate households that are more sensitive to external factors such as weather conditions or economic fluctuations. By recognizing these seasonal trends, utilities and policymakers can implement timely interventions to mitigate energy demand during peak periods and promote load balancing across different seasons.

However, it is essential to acknowledge some limitations of the clustering analysis approach. The clustering results are highly dependent on the choice of clustering algorithm and the number of clusters selected. While the elbow method was used to determine the optimal number of clusters in this study, alternative methods such as silhouette analysis or hierarchical clustering could yield different results. Additionally, the clustering process relies on the quality and representativeness of the input data, which may be influenced by factors such as data availability, accuracy, and completeness.

VII. CONCLUSION

In conclusion, the classification and analysis of users' electricity consumption behavior using cluster analysis algorithms provide a valuable framework for understanding the complex dynamics of energy usage among residential consumers. Through the systematic application of clustering techniques, this study has identified distinct consumer segments with unique consumption patterns, including variations in daily consumption levels, peak usage times, and seasonal trends. These insights offer utilities and policymakers a deeper understanding of the drivers behind electricity consumption behavior, enabling the development of targeted interventions to promote energy efficiency and sustainability.

Moving forward, the findings of this study underscore the importance of adopting a segmented approach to energy management, wherein tailored strategies are devised to address the specific needs and preferences of different consumer segments. By leveraging clustering analysis, utilities can optimize resource allocation, implement demand-side management strategies, and design targeted energy-saving programs that resonate with the diverse consumer base. Moreover, continued research in this field, incorporating advanced clustering techniques and additional socio-economic and environmental factors, holds the potential to further enhance our understanding of electricity consumption behavior and inform the development of innovative solutions to address emerging challenges in energy sustainability and environmental conservation.

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