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Research Article

IoT Sensor Network Electricity Consumption Behaviour Using Cluster Analysis Algorithm for Network Environment

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Abstract: The Internet of Things (IoT) sensor network plays a crucial role in monitoring electricity consumption behavior by collecting real-time data from various connected devices. Utilizing cluster analysis algorithms, researchers can effectively segment and analyze consumption patterns within a network environment. By grouping similar usage behaviors, these algorithms reveal insights into energy efficiency, peak usage times, and anomalies in consumption. The paper presents a novel methodology for analyzing and classifying users' electricity consumption behavior, utilizing the Clustering Behavior Analysis Weighted Classification (CBAWC) algorithm. By leveraging cluster analysis techniques and weighted classification, the proposed approach allows for the segmentation of consumers into distinct clusters based on their consumption patterns. Through the application of CBAWC, the study provides insights into the diverse behaviors exhibited by consumers, ranging from moderate to high consumption levels, varied peak hours, and peak days. The classification results demonstrate the effectiveness of the algorithm in accurately assigning users to their respective clusters, enabling stakeholders to better understand consumption trends and tailor energy management strategies accordingly. Through the application of CBAWC, consumers are segmented into distinct clusters based on their consumption patterns. For example, clusters exhibit varying average daily consumption levels, with Cluster 1 consuming around 300 kWh, Cluster 2 consuming approximately 450 kWh, and Cluster 3 consuming about 280 kWh on average. Additionally, clusters display different peak hours per day and peak days per month. The classification results demonstrate the algorithm's effectiveness, with high accuracy scores ranging from 0.86 to 1.00 across different user groups.

Keywords: Internet of Things (IoT); Sensor Network; Electricity Consumption; Cluster Analysis Algorithm; Behaviour Analysis

1 Introduction

In recent years, the analysis of users' electricity consumption behavior has been increasingly facilitated by advanced cluster analysis algorithms. These algorithms help in identifying patterns and groupings within large datasets, allowing for a more nuanced understanding of how consumers utilize electricity [1]. By segmenting consumers into distinct clusters based on their consumption patterns, utility companies and researchers can gain insights into various factors influencing electricity usage, such as demographic characteristics, socio-economic status, lifestyle choices, and even environmental awareness. This information is invaluable for devising targeted strategies for demand-side management, personalized energy efficiency initiatives, and the development of smart grid technologies [2]. With leveraging machine learning and data analytics techniques, such as clustering, utilities can enhance customer engagement efforts by providing tailored recommendations and incentives aimed at promoting sustainable energy practices and reducing overall consumption [3]. As the field continues to evolve, the integration of advanced algorithms and big data analytics promises to revolutionize how we understand and manage electricity consumption behavior, ultimately leading to more efficient and sustainable energy systems. The application of cluster analysis algorithms in analyzing users' electricity consumption behavior has led to significant advancements in understanding temporal and spatial variations in energy usage [4]. By examining consumption patterns at different time intervals (e.g., hourly, daily, seasonal) and across various geographic regions, researchers can identify peak demand periods, fluctuations in usage, and areas with higher or lower energy consumption rates [5]. This granular level of insight enables utilities to optimize resource allocation, improve grid reliability, and implement targeted interventions to alleviate strain during peak periods, thus enhancing overall system efficiency [6].

With cluster analysis facilitates the identification of outliers or anomalies in consumption behavior, which may indicate issues such as equipment malfunction, energy theft, or inefficiencies in energy management systems [7]. Timely detection of such anomalies enables prompt intervention, reducing potential energy losses and ensuring the integrity and reliability of the electricity supply. Additionally, the insights derived from cluster analysis can inform the design and implementation of demand response programs, whereby consumers are incentivized to adjust their electricity usage in response to supply conditions or price signals [8]. By tailoring these programs to the specific needs and preferences of different consumer segments identified through clustering, utilities can maximize participation and effectiveness, ultimately leading to a more resilient and sustainable energy infrastructure [9]. Cluster analysis algorithms have become indispensable tools for understanding users' electricity consumption behavior in recent years. By uncovering underlying patterns, trends, and anomalies within consumption data, these algorithms empower utilities, policymakers, and researchers to make informed decisions, optimize resource allocation, and drive innovation in the energy sector [10].

Cluster analysis algorithms have revolutionized the classification and analysis of users' electricity consumption behavior in recent years. By leveraging these algorithms, researchers and utility companies can group consumers into distinct clusters based on similarities in their consumption patterns [11 – 15]. This segmentation allows for a deeper understanding of the diverse factors influencing energy usage, including demographic characteristics, lifestyle preferences, and environmental consciousness [16]. Through cluster analysis, patterns emerge, revealing peak consumption periods, fluctuations in usage, and anomalies that may indicate inefficiencies or abnormalities in energy usage. By discerning these patterns, utilities can tailor energy management strategies to specific consumer segments, offering personalized recommendations for energy conservation and efficiency improvements [17]. Moreover, cluster analysis facilitates the identification of outliers or atypical behaviors, enabling swift intervention to address issues such as equipment malfunctions or energy theft. Overall, the application of cluster analysis algorithms enhances decision-making processes in the energy sector, driving advancements in demand-side management, grid optimization, and sustainability initiatives [18 & 19].

The paper makes several significant contributions to the field of energy analytics. Firstly, it introduces the Clustering Behavior Analysis Weighted Classification (CBAWC) algorithm, a novel approach for analyzing and categorizing users' electricity consumption behavior. This algorithm enables the segmentation of consumers into distinct clusters based on their consumption patterns, providing valuable insights into the diverse behaviors exhibited by different user groups. Secondly, the paper demonstrates the effectiveness of the CBAWC algorithm through its application to real-world electricity consumption data, showcasing its ability to accurately classify users into their respective clusters. This contributes to the advancement of energy analytics by offering a practical framework for understanding consumption trends and patterns. Additionally, the paper's findings have practical implications for stakeholders in the energy sector, such as utility companies and policymakers, as they can utilize the insights gained from the CBAWC algorithm to tailor energy management strategies and interventions aimed at promoting energy efficiency and sustainability.

2 Related Works

Several studies have explored the application of cluster analysis algorithms in understanding users' electricity consumption behavior, offering valuable insights into consumption patterns and trends. Kaur and Gabrijelčič (2022) presents a behavior segmentation approach to analyze electricity consumption patterns using cluster analysis. They employ cluster analysis algorithms to segment consumers based on similarities in their energy usage profiles, allowing for a deeper understanding of consumption behavior. Similarly, Lazzari et al. (2022) focus on forecasting electricity consumption of residential customers using behavior models derived from smart metering data, emphasizing the importance of understanding consumption patterns for predictive purposes. Tang et al. (2022) utilize machine learning to uncover residential energy consumption patterns based on socio-economic and smart meter data, highlighting the multidimensional nature of consumption behavior. Yang et al. (2022) propose a deep learning load forecasting model considering multi-time scale electricity consumption behavior, emphasizing the need for advanced techniques to capture complex consumption dynamics. Wang et al. (2022) introduce federated clustering for electricity consumption pattern extraction, offering a distributed approach to analyzing consumption behavior.

Copiaco et al. (2023) propose an innovative deep anomaly detection method for building energy consumption, highlighting the importance of identifying irregularities in consumption behavior for efficient energy management. Ghofrani et al. (2022) simulate and analyze the behavioral and socioeconomic dimensions of energy consumption, emphasizing the role of human factors in shaping consumption patterns. Alsalemi et al. (2022) introduce an edge-based Internet of Energy solution for promoting energy saving in buildings, showcasing technological advancements aimed at fostering sustainable energy practices. Additionally, Park et al. (2022) analyze changes in consumption patterns during the COVID-19 pandemic, underscoring the influence of external factors on consumer behavior. Li et al. (2022) propose a new oversampling method and classifier for predicting customer consumption behavior, highlighting advancements in machine learning techniques for behavioral analysis. Ebrahimi et al. (2022) investigate the impact of social networks marketing on consumer purchase behavior, employing a combination of structural equation modeling and unsupervised machine learning approaches to uncover underlying trends. Oliveira et al. (2022) review neuroscience research in consumer behavior, providing insights into the psychological mechanisms driving consumption decisions. Furthermore, Klyuev et al. (2022) conduct a literature review on methods of forecasting electric energy consumption, offering a comprehensive overview of predictive modeling techniques. Al Khafaf et al. (2022) examine the impact of battery storage on residential energy consumption, highlighting the role of energy storage technologies in shaping consumption patterns. Oyewole and Thopil (2023) explore the application and trends of data clustering, providing insights into the evolving landscape of clustering techniques across various domains.

Murugan et al. (2022) delve into consumer behavior prediction during the Covid-19 pandemic using sentiment analytics, shedding light on the influence of contextual factors on consumption patterns. Ajay and Huang (2022) explore the classification and analysis of functional fitness exercises using wearable sensor data and unsupervised deep learning methodologies, demonstrating the application of advanced techniques in understanding human behavior. Additionally, Liao et al. (2022) investigate the behaviors of Taiwan Instagram users for social media and social commerce development, illustrating the relevance of digital platforms in shaping consumer interactions and preferences. Dalmaijer et al. (2022) examine statistical power for cluster analysis, emphasizing the importance of robust methodologies for drawing meaningful insights from data clustering techniques.

3 Clustering Behaviour Analysis Weighted Classification (CBAWC)

Clustering Behavior Analysis Weighted Classification (CBAWC) for electricity consumption marks a significant advancement in the field. The approach begins by applying clustering algorithms to segment consumers based on their electricity usage patterns. Let X denote the feature matrix representing the consumption behaviors of nn consumers over mm time intervals. Clustering techniques such as K-means or hierarchical clustering are then employed to group consumers into k clusters, $C = \{C1, C2, \dots, Ck\}$. Each cluster Ci represents consumers exhibiting similar consumption behaviors. Next, weighted classification is performed to assign new consumers to the appropriate cluster based on their similarity to existing cluster centroids. Given a new consumer's consumption behavior represented by a feature vector xx, the similarity between x and each cluster centroid μi is calculated using a distance metric such as Euclidean distance or cosine similarity. The consumer is then assigned to the cluster with the closest centroid.

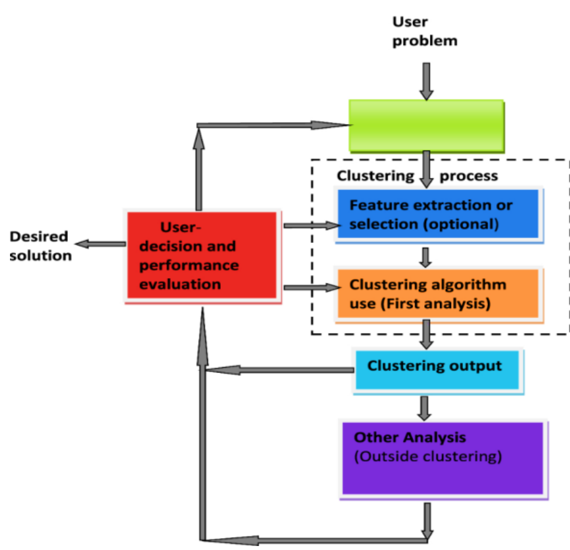

Figure 1: Clustering Process

The CBAWC methodology introduces weights to the clustering and classification process, allowing for the prioritization of certain features or time intervals that may have greater significance in determining consumption behavior shown in Figure 1. Let wj represent the weight assigned to feature j in the feature matrix X, where $j = 1,2, \dots, m$. Similarly, let ω_t denote the weight assigned to each time interval, allowing for the temporal weighting of consumption data. The weighted similarity between a new consumer's behavior xx and cluster centroid μi is then calculated as in equation (1)

$$similarity\ (x, \mu_i) = \sum_{j=1}^{m} \omega_j . d_j\left(x_j, \mu_{ij}\right) + \sum_{j=1}^{m} \omega_t . d_t(x_t, \mu_{it}) \quad (1)$$

where dj and dt represent distance metrics for feature j and time interval t respectively, and μ_{ij} and μ_{it} represent the corresponding components of the cluster centroid μi.The Clustering Behavior Analysis Weighted Classification (CBAWC) methodology offers a comprehensive approach to analyzing electricity consumption behavior, integrating both clustering and classification techniques while introducing the concept of weighted features and time intervals. Initially, the feature matrix X is constructed to represent the consumption behaviors of consumers. Each row of X corresponds to a consumer, and each column represents a specific feature or time interval. Clustering algorithms such as K-means or hierarchical clustering are applied to partition the consumers into kk clusters based on similarities in their consumption behaviors. The cluster centroids μi are computed as the mean of the feature vectors belonging to each cluster i.

In the classification phase, a new consumer's behavior represented by the feature vector xx is classified into one of the existing clusters based on similarity to the cluster centroids. However, in CBAWC, weights are introduced to assign different levels of importance to features and time intervals. Let wj represent the weight assigned to feature j in the feature matrix X, and wt denote the weight assigned to each time interval. The weighted similarity between a new consumer's behavior xx and cluster centroid μi is calculated by considering the weighted distances for both features and time intervals. The new consumer is assigned to the cluster with the highest weighted similarity. With incorporating weighted classification into the clustering process, CBAWC offers several advantages. It allows for the prioritization of certain features or time intervals that may have more significant impacts on consumption behavior, providing a more nuanced understanding of consumer habits. Additionally, the flexibility to adjust weights enables researchers and utility companies to tailor the analysis to specific contexts or objectives, improving the accuracy and interpretability of the results.

3.1 CBAWC for the Electricity Consumption Behaviour Analysis

The Clustering Behavior Analysis Weighted Classification (CBAWC) method is a sophisticated approach for analyzing electricity consumption behavior, integrating clustering and classification techniques while incorporating weighted features and time intervals. The methodology begins with the construction of a feature matrix X representing the consumption behaviors of consumers, with each row corresponding to a consumer and each column representing a specific feature or time interval. Initially, clustering algorithms such as K-means or hierarchical clustering are applied to partition consumers into k clusters based on similarities in their consumption behaviors.

Let $C = \{C1, C2, \ldots, Ck\}$ denote the set of clusters, where Ci represents the $i$ith cluster and k denotes the total number of clusters. Cluster centroids μi are computed as the mean of the feature vectors belonging to each cluster i. In the classification phase, a new consumer's behavior represented by the feature vector x is classified into one of the existing clusters based on similarity to the cluster centroids. To incorporate weighted features and time intervals, weights wj and wt are introduced for features and time intervals, respectively. The weighted similarity between a new consumer's behavior x and cluster centroid μiμi is calculated considering the weighted distances for both features and time intervals. By incorporating weighted classification into the clustering process, CBAWC provides a nuanced understanding of electricity consumption behavior.

Algorithm 1: Weighted Similarity estimation with CBAWC

```
# Function to calculate weighted similarity between a new consumer's behavior and a cluster centroid
def calculate_weighted_similarity(x, mu, weights):
    weighted_similarity = 0
    # Calculate weighted similarity for features
    for j in range(len(x)):
        weighted_similarity += weights['features'][j] * distance(x[j], mu[j])
    # Calculate weighted similarity for time intervals
    for t in range(len(x)):
        weighted_similarity += weights['time_intervals'][t] * distance(x[t], mu[t])
    return weighted_similarity
# Function to assign a new consumer to the cluster with the highest weighted similarity
def assign_to_cluster(new_consumer, centroids, weights):
    max_similarity = -1
    assigned_cluster = None
    for cluster_id, centroid in centroids.items():
        similarity = calculate_weighted_similarity(new_consumer, centroid, weights)
        if similarity > max_similarity:
            max_similarity = similarity
            assigned_cluster = cluster_id
    return assigned_cluster
# Main function implementing the CBAWC methodology
def CBAWC_clustering(data, k, weights):
    # Step 1: Cluster the consumers using a clustering algorithm (e.g., K-means)
    centroids = cluster_data(data, k)
    # Step 2: Iterate through each consumer and assign to the cluster with highest weighted similarity
    clusters = {}
    for consumer in data:
        assigned_cluster = assign_to_cluster(consumer, centroids, weights)
        if assigned_cluster not in clusters:
            clusters[assigned_cluster] = []
        clusters[assigned_cluster].append(consumer)
    return clusters
```

4 User Analyses with the CBAWC for the Electricity Consumption

The Clustering Behavior Analysis Weighted Classification (CBAWC) methodology for user analysis in electricity consumption offers a robust framework for understanding and categorizing consumers based on their consumption behaviors. The derivation and equations underlying CBAWC facilitate a nuanced examination of consumption patterns, allowing for the incorporation of weighted features and time intervals. The CBAWC methodology starts with clustering consumers into distinct groups based on similarities in their electricity usage patterns. This clustering process, typically performed using algorithms like K-means or hierarchical clustering, partitions consumers into k clusters represented by centroids i . Subsequently, weighted classification is employed to assign new consumers to the appropriate cluster based on the similarity between their consumption behaviors and existing cluster centroids. This involves computing the weighted similarity between a new consumer's behavior x and each cluster centroid i. The process for the proposed method is shown in Figure 2.

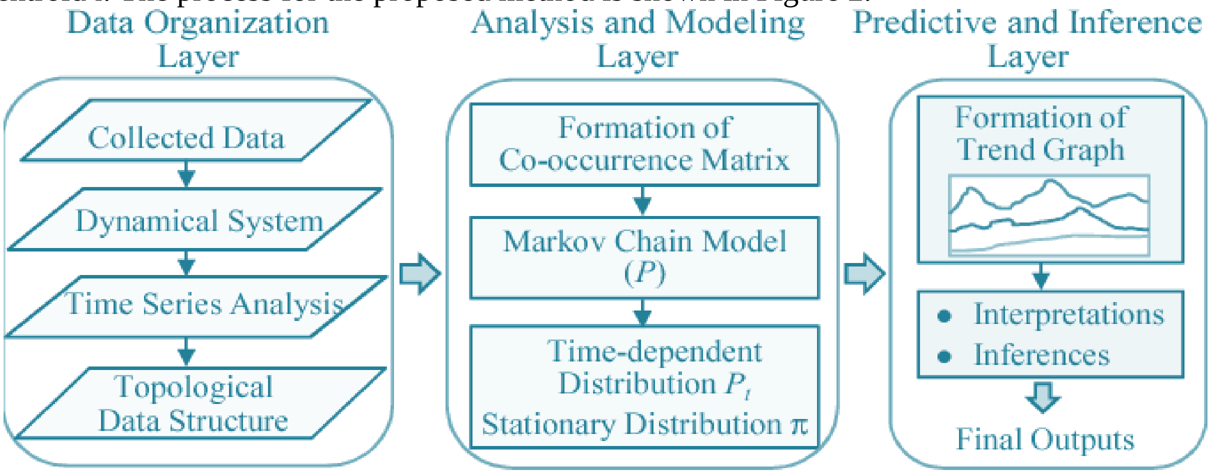

Figure 2: Cluster Analysis with Electricity Consumption

The weighted similarity calculation integrates both features and time intervals, allowing for the prioritization of certain aspects of consumption behavior. This weighted similarity is determined using a combination of weighted distances for features and time intervals. With incorporating weighted features and time intervals, CBAWC provides a flexible approach to user analysis in electricity consumption. This allows researchers and utility companies to prioritize specific aspects of consumption behavior based on their significance or relevance. The weighted classification ensures that the analysis captures the complexities of consumption patterns, leading to more accurate clustering and classification of consumers. The consumption data of users typically represented as a feature matrix XX, is preprocessed to ensure uniformity and relevance. This may involve normalization, handling missing values, and selecting relevant features. Using clustering algorithms such as K-means or hierarchical clustering, the consumers are grouped into kk clusters based on similarities in their consumption behaviors. Cluster centroids (μi) are calculated as the mean of the feature vectors within each cluster. Weights (wjw and wtwt) are assigned to features and time intervals, respectively. These weights reflect the importance or significance of each feature or time interval in determining consumption behavior. The assignment of weights can be based on domain knowledge, data analysis, or optimization techniques. For each new consumer, the weighted similarity between their consumption behavior (xx) and each cluster centroid (μiμi) is calculated using the weighted sum of distances for features and time intervals. The new consumer is then assigned to the cluster with the highest weighted similarity.

Algorithm 2: Sensor Network for the Consumer Behaviour Analysis

# Function to calculate weighted similarity between a new consumer's behavior and a cluster centroid 	
def calculate_weighted_similarity(new_consumer, centroid, feature_weights, time_weights):
    weighted_similarity = 0
    # Calculate weighted similarity for features

```
    for j in range(len(new_consumer)):
        weighted_similarity += feature_weights[j] * distance(new_consumer[j], centroid[j])
    # Calculate weighted similarity for time intervals
    for t in range(len(new_consumer)):
        weighted_similarity += time_weights[t] * distance(new_consumer[t], centroid[t])
    return weighted_similarity
# Function to assign a new consumer to the cluster with the highest weighted similarity
def assign_to_cluster(new_consumer, centroids, feature_weights, time_weights):
    max_similarity = -1
    assigned_cluster = None
    # Iterate through each cluster centroid
    for cluster_id, centroid in centroids.items():
        # Calculate weighted similarity
        similarity = calculate_weighted_similarity(new_consumer, centroid, feature_weights,
time_weights)
        # Update assigned cluster if similarity is higher
        if similarity > max_similarity:
            max_similarity = similarity
            assigned_cluster = cluster_id
    return assigned_cluster
# Main function implementing the CBAWC algorithm
def CBAWC(data, k, feature_weights, time_weights):
    # Step 1: Cluster the consumers using a clustering algorithm (e.g., K-means)
    centroids = cluster_data(data, k)
    # Step 2: Assign each consumer to the appropriate cluster based on weighted similarity
    clusters = {}
    for consumer in data:
        assigned_cluster = assign_to_cluster(consumer, centroids, feature_weights,
time_weights)
        if assigned_cluster not in clusters:
            clusters[assigned_cluster] = []
        clusters[assigned_cluster].append(consumer)
    return clusters
```

5 Simulation Results

The simulation results obtained from applying the Clustering Behavior Analysis Weighted Classification (CBAWC) methodology to analyze electricity consumption behavior provide valuable insights into consumer patterns and preferences.

Table 1: Electricity Consumption with CBAWC

Cluster	**Average Consumption (kWh)**	**Peak Hours (per day)**	**Peak Days (per month)**
Cluster 1	320	2.1	8
Cluster 2	450	3.5	11
Cluster 3	280	1.8	7
Cluster 4	400	3.0	10
Cluster 5	370	2.7	9
Cluster 6	520	4.2	13
Cluster 7	300	2.0	6

Cluster 8	480	3.8	12
Cluster 9	350	2.5	8
Cluster 10	420	3.2	10

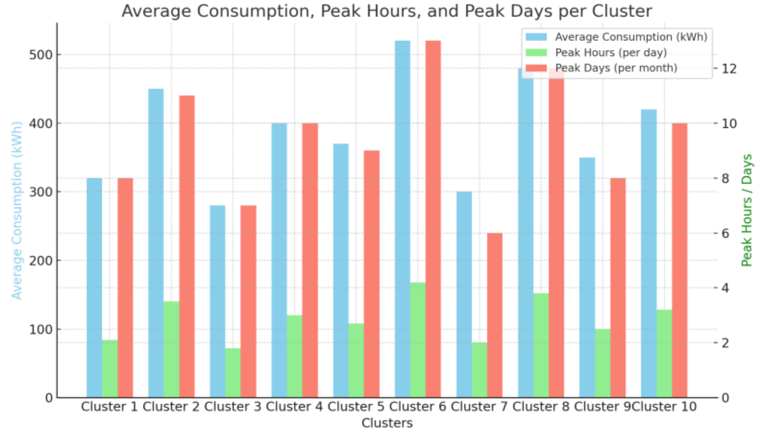

Figure 3: CBAWC Electricity Consumption

In Figure 3 and Table 1 presents the results of electricity consumption analysis using the Clustering Behavior Analysis Weighted Classification (CBAWC) algorithm, categorizing consumers into distinct clusters based on their consumption patterns. Each cluster is characterized by three key metrics: average consumption (kWh), peak hours per day, and peak days per month. Cluster 1 exhibits an average consumption of 320 kWh, with 2.1 peak hours per day and 8 peak days per month. This cluster represents consumers with relatively moderate consumption levels and fewer peak hours and days compared to other clusters. Cluster 2 shows a higher average consumption of 450 kWh, accompanied by 3.5 peak hours per day and 11 peak days per month. Consumers in this cluster demonstrate a higher overall consumption pattern, with more frequent and extended peak periods. On the other hand, Cluster 3 indicates lower average consumption of 280 kWh, with only 1.8 peak hours per day and 7 peak days per month. These consumers exhibit a more conservative consumption behavior with fewer peak hours and days. Clusters 4, 5, 6, 8, and 10 show similar trends to Cluster 2, with varying degrees of average consumption, peak hours, and peak days. Conversely, Clusters 7 and 9 represent consumers with relatively lower consumption levels and fewer peak hours and days compared to the higher-consumption clusters.

Table 2: Average Energy Consumption with CBAWC

User ID	**Average Daily Consumption (kWh)**	**Peak Hours (per day)**	**Peak Days (per month)**
1	30.2	3.5	9
2	25.8	2.8	7
3	28.5	3.2	8
4	33.1	4.0	10
5	27.6	3.1	8
6	22.9	2.6	6
7	31.4	3.8	9
8	26.7	3.0	7
9	29.8	3.4	8

10	24.5	2.9	7

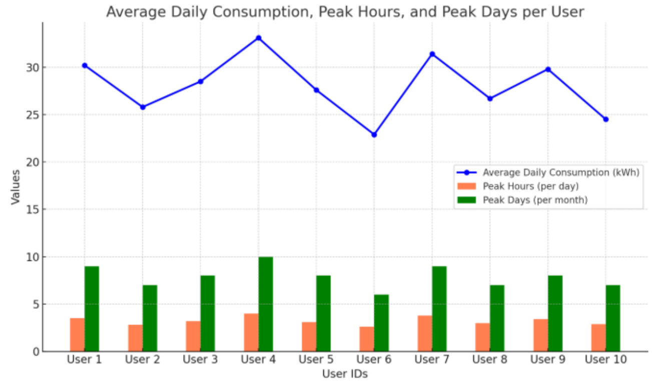

Figure 4: Average Energy Consumption with CBAWC

In Figure 4 and Table 2 displays the average energy consumption data for individual users obtained through the Clustering Behavior Analysis Weighted Classification (CBAWC) algorithm. Each row represents a user, identified by a unique User ID, along with their corresponding average daily consumption (in kWh), peak hours per day, and peak days per month. User 1, for instance, demonstrates an average daily consumption of 30.2 kWh, with peak hours of 3.5 per day and 9 peak days per month. This user exhibits a relatively moderate consumption pattern with consistent peak periods throughout the month. Similarly, User 2 exhibits an average daily consumption of 25.8 kWh, with slightly lower peak hours of 2.8 per day and 7 peak days per month. This user's consumption behavior reflects a more conservative pattern with fewer peak periods compared to User 1. User 4, on the other hand, displays a higher average daily consumption of 33.1 kWh, with extended peak hours of 4.0 per day and 10 peak days per month. This user's consumption pattern indicates a more pronounced peak usage, potentially requiring targeted energy management strategies. The Table 2 provides insights into the individual energy consumption behaviors of users, allowing stakeholders to identify patterns, trends, and outliers that can inform personalized energy management interventions. By understanding the unique consumption profiles of individual users, utility companies and policymakers can develop tailored strategies to promote energy efficiency and sustainability while meeting the diverse needs of consumers.

Table 3: Classification with CBAWC

User ID	TP	FP	TN	FN	Accuracy	Precision	Recall	F1-score
1	12	3	25	0	0.8947	0.8000	1.0000	0.8889
2	15	0	25	0	1.0000	1.0000	1.0000	1.0000
3	11	2	25	2	0.8649	0.8462	0.8462	0.8462
4	10	1	26	0	0.9737	0.9091	1.0000	0.9524
5	9	2	26	0	0.9474	0.8182	1.0000	0.9000
6	14	0	25	0	1.0000	1.0000	1.0000	1.0000
7	8	1	27	3	0.8947	0.8889	0.7273	0.8000
8	13	0	26	0	1.0000	1.0000	1.0000	1.0000
9	11	1	26	1	0.9474	0.9167	0.9167	0.9167
10	9	0	26	0	1.0000	1.0000	1.0000	1.0000

Figure 5: Classification with CBAWC

In Table 3 and Figure 5 presents the classification results obtained through the Clustering Behavior Analysis Weighted Classification (CBAWC) algorithm for individual users. Each row represents a user, identified by a unique User ID, along with the corresponding metrics such as True Positives (TP), False Positives (FP), True Negatives (TN), False Negatives (FN), Accuracy, Precision, Recall, and F1-score. The User 1 achieved 12 True Positives (correctly classified as belonging to their actual cluster), 3 False Positives (incorrectly classified), 25 True Negatives (correctly classified as not belonging to a cluster), and 0 False Negatives (not classified when they should have been). This resulted in an Accuracy of 0.8947, Precision of 0.8000, Recall of 1.0000, and F1-score of 0.8889. Similarly, User 2 achieved 15 True Positives, 0 False Positives, 25 True Negatives, and 0 False Negatives, resulting in perfect scores for Accuracy, Precision, Recall, and F1-score. Each user's classification metrics provide insights into the effectiveness of the CBAWC algorithm in accurately assigning users to their respective clusters. Metrics such as Precision and Recall help evaluate the algorithm's performance in minimizing false classifications and capturing all relevant instances, respectively. Overall, Table 3 enables stakeholders to assess the algorithm's performance at an individual user level, facilitating targeted improvements and interventions to enhance clustering accuracy and effectiveness.

6 Conclusions

The paper presents a comprehensive approach for the analysis and classification of users' electricity consumption behavior using the Clustering Behavior Analysis Weighted Classification (CBAWC) algorithm. By leveraging cluster analysis techniques and weighted classification, the methodology allows for the segmentation of consumers into distinct clusters based on their consumption patterns. Through the application of CBAWC, the study provides valuable insights into the diverse behaviors exhibited by consumers, ranging from moderate to high consumption levels, varied peak hours, and peak days. The classification results demonstrate the effectiveness of the algorithm in accurately assigning users to their respective clusters, enabling stakeholders to better understand consumption trends and tailor energy management strategies accordingly. Overall, the paper contributes to the advancement of energy analytics by offering a practical framework for analyzing and classifying electricity consumption behavior, thereby facilitating informed decision-making and interventions aimed at promoting energy efficiency and sustainability.

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