An Analysis of Electrical Energy Usage in Social Consumers Using Fuzzy C Means

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***Abstract*— The objective of this study is to examine the patterns of electrical energy usage in social consumers by employing the Fuzzy C Means clustering method to assist utility companies in the development of business strategies, operations, planning, and energy policies that are customized to the specific needs of each group. The problem of unpredictable social activities, changes in work patterns, and community activities, particularly among social consumers, result in significant declines and irregular electricity consumption patterns. It is crucial for energy providers to comprehend these evolving patterns to effectively manage electricity supplies. This research was carried out in a 5-step process, namely Data Collection, Data Preprocessing, Clustering Process with Fuzzy C Means (FCM), find pattern and clustering validity. This study sources its data from the Automatic Meter Reading (AMR) of social consumers, specifically places of worship, educational institutions, and health services. We employ the Fuzzy C Means (FCM) Clustering method to categorize electrical energy consumption patterns into multiple groups, considering similarities in the data. The variables utilized in this analysis are kilowatt (kW) and kilovolt-ampere (kVA). The findings indicate that places of worship, educational institutions, and health services exhibit distinct patterns of electrical energy usage, although belonging to the same electricity tariff category. The quality of cluster results in this research using the Davies-Bouldin index (DBI) method is 0.51, which shows that the resulting clustering has a fairly good level of separation and compactness.**

Keywords — Clustering, Fuzzy C Means, Electrical Energy Consumptions, Pattern, Davies–Bouldin index

I. INTRODUCTION

Analyzing energy consumption for low-voltage customers poses a significant difficulty due to their substantial variability [1]. In Indonesia, there are five distinct categories of electrical energy consumers: household, industry, business, social, and public. Analyzing energy use patterns in each category presents unique challenges. The energy consumption patterns of each category of electricity customers are contingent upon the user's activities and operating hours. Various factors, such as unpredictable social activities, changes in work patterns, and community activities, particularly among social customers, contribute to irregular consumption patterns, which in turn result in significant decreases in electricity consumption. In addition, changes in the pattern of electricity use during social events or community gatherings can lead to an increase in electricity consumption at specific times. It is important to comprehend shifts in electricity usage patterns in order for electrical energy providers to effectively anticipate and regulate electricity supplies [2]. Recognizing electrical energy usage trends can assist electricity supply utility company in better planning and management of their network infrastructure. In addition, it can avoid service outages and overload by optimizing network capacity to predict possible consumption surges [3].

Several types of social customers, including places of worship, educational institutions and health services, have different electricity usage patterns due to their unique characteristics and operational needs. These differences highlight the importance of conducting specific analyzes for each type of social customer to design effective energy management strategies. Identify these varying patterns of electricity use can help in planning more efficient infrastructure and developing targeted energy savings programs [4].

Clustering is an effective data analysis method for identifying patterns of electrical energy use by grouping consumption data based on certain similarities [5]. In the context of electrical energy consumption, clustering can help identify groups of customers with similar usage patterns, thereby facilitating energy infrastructure analysis and planning. Energy consumption data obtained from Automatic Meter Reading (AMR) can be grouped based on time of use, frequency and intensity of consumption. This makes it possible to view daily, weekly or seasonal consumption patterns, which can be used to optimize energy distribution and plan more efficient network capacity [3], [6].

The clustering approach that will be employed in this study is Fuzzy C Means (FCM). FCM is one of effective clustering approach for discovering patterns of electrical energy consumption [5]. In this research, FCM used to detect electricity consumption trends that cannot be effectively addressed by conventional clustering techniques. FCM works with assigning a membership degree to each data point, enabling them to belong to many clusters simultaneously. Other research that has been conducted by Liu et al, using the FCM method was able to distribute unbalanced data in electricity load consumption patterns [7]. This is especially useful in the analysis of complex data, such as electrical energy consumption patterns, where usage behaviour frequently overlaps and cannot be easily classified in a binary manner. Recent research conducted by Yang et al, using the FCM method to cluster interval valued time series, shows that further research is needed to overcome problems with data with the interval time series type [8]. Based on the problems above, this research will conduct an analysis of the use of electrical energy specifically in social groups using FCM to identify energy consumption patterns in social group groups such as places of worship, educational institutions and health services.

In this research “An Analysis of Electrical Energy Usage in Social Consumers Using Fuzzy C Means" aims to overcome the limitations of previous research with a simpler, more efficient and more relevant approach in the context of social energy consumption. Thus, it is hoped that this research can provide more applicable and useful solutions for planning and managing electricity network infrastructure and can contribute to the basis for further studies in the field of energy consumption analysis, especially in developing and refining clustering algorithms for other applications in the energy sector and can practically become a tool for electricity service providers to increase the efficiency and reliability of energy systems.

II. LITERATURE REVIEW

A. Related Works

Research was conducted by Cen et al in 2022 regarding Electricity Pattern Analysis by Clustering Domestic Load Profiles Using Discrete Wavelet Transform using FCM as one of the cluster analysis methods carried out [9]. The research reports the quality of the cluster results with a DBI value of 0.78. Furthermore in 2023, Okereke et al using the K-Means clustering method to group consumers based on similarities in their electricity consumption behaviour. This research shows that K-Means can help electricity company to understand electricity consumers based on the resulting clusters [3]. However, based on the characteristics of the data in this research, which is in the form of time series data which has high variability and uncertainty which is very complex to analyse, such as fluctuations that occur periodically in certain time intervals, such as weekly, monthly or annually, it requires an analytical method that is capable of handles this uncertainty by providing fuzzy membership degrees that reflect the probability that certain data can fall into several clusters. In 2024, Lai Jian et al utilize the FCM clustering algorithm to categorize a user's usual daily load curve and create a "portrait" of the user's electricity consumption behaviour. This portrait will be employed to identify fraudulent activities in the utilization of electrical energy [10]. In early 2024 Yang et al, used FCM to group time series data that have certain intervals as a typical shape-based clustering algorithm, the results showed superior performance based on comparative experiments [8].

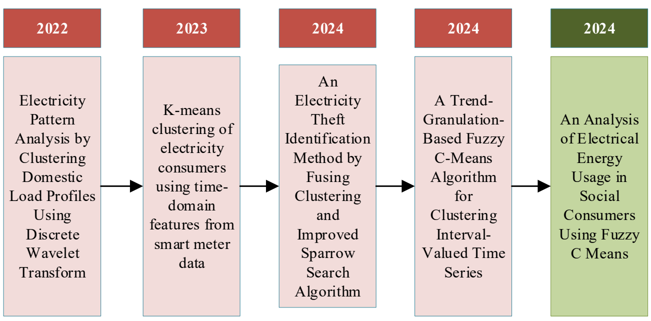

Fig. 1. Related work

Fig. 1 shows the literature related to this research from 2022 to 2024. This research presents substantial novel contributions compared to earlier studies, including::

1. Focus on Social Consumers, different from previous research which focused on domestic or general consumers [3], [9], this research targets social consumers such as places of worship, educational institutions and health services, which have unique needs and consumption patterns.
2. The use of Fuzzy C-Means (FCM) offers a more flexible and refined approach compared to hard clustering methods such as K-means, and can handle data with partial membership [3].
3. This research not only groups data [8], [10] but also has the potential to provide practical recommendations for planning and managing electricity networks, taking into account operational and social aspects of the consumers studied.

B. Clustering

Clustering is an important technique in machine learning and data mining that can be applied to various types of data, including time series data, text, images, and other multidimensional data [5]. The main purpose of clustering is to group data into several groups or clusters based on similar characteristics or features of the data used

C. Fuzzy Clustering Means (FCM)

Fuzzy clustering analysis has proven to be effective in various domains such as large-scale data analysis, data mining, picture analysis, pattern identification, and information fusion. Among the numerous fuzzy clustering algorithms, the Fuzzy C-means (FCM) clustering algorithm is the most widely and successfully deployed [11]. This method has a simple structure, low computational complexity, and is easy to implement. FCM has been widely used in electric power system clustering research [12] which allows more flexible grouping of data and can provide a better understanding of the relationships between clusters and samples [13]. The following are functions in the FCM algorithm [14], [15]:

$$Jm = \sum_{i=1}^{n} \sum_{j=1}^{c} U_{ij}^{m} D_{ij}^{2} \quad (1)$$

Steps of FCM [11], [16]:
Step 1: Determine the number of clusters C, initialize cluster center matrix V (0) with random values based on the original data.
Step 2: Initialize the membership matrix U(0):

$$Uij^{(t)} = \frac{1}{\sum_{k=1}^{c} \left(\frac{dij(t)}{dkj(t)} \right)^{\frac{2}{m-1}}} \quad (2)$$

$dij = ||xj - vi||^2$ is the distance xi and cluster centre vi
Step 3: Determine the new cluster centre matrix:

$$vi(t+1) = \frac{\sum_{j=1}^{n} u_{ij}^{m} * xj}{\sum_{j=1}^{c} u_{ij}^{m}(t)} \quad (3)$$

Step 4: Determine the membership matrix Uij in function (2)
Step 5: If max $\{|ui(t+1) - uij\ (t)|\} <$ ε then stop, otherwise go to Step 3 and continue until max iteration.

In the FCM algorithm, fuzzy membership can cause overlap in cluster data so that members of two clusters can be members of the same two clusters with different degrees of membership [17]. The presence of noise in a dataset significantly impacts the entire process of clustering categorization. Currently, numerous algorithms are unable to handle noise, resulting in negative impact on the categorization of the dataset. The outcomes of the noise processing are disappointing. The processing of noise data is either excessively intricate or does not have a significant impact on noise reduction. These factors contribute to the limitations of the FCM clustering technique in actual applications [11].

D. Davies-Bouldin index (DBI)

DBI is a method commonly used to evaluate clustering quality and find the optimal number of clusters in a dataset The following is function of DBI [12], [18]:

$$DBI = \frac{1}{k}\sum_{i=1}^{k} \max i \neq j \frac{si+sj}{Mij} \qquad (4)$$

A lower DB value indicates better clustering quality and a better optimal number of clusters [19].

III. Research Method

The research method shown in Fig. 2

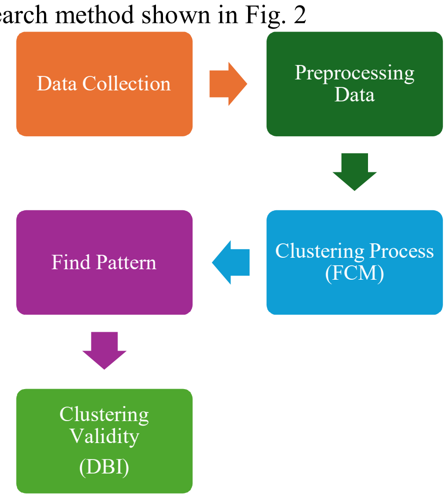

Fig. 2. Research Method

Based on Fig 2, clustering process implemented in 5 stage as follows:

1. Data collecting on electricity consumption with the variables Kilowatt (kW) and Kilovolt-Ampere (kVA) for social group customers, namely Places of worship, educational institutions, and health services. data obtained from Automatic Meter Reader (AMR)
2. Data preprocessing is carried out by making the same data interval, namely every 1 hour in weekly and monthly, cleaning the data from missing values. Missing values in the data can occur if unstable conditions occur during data recording when sending data from AMR to the database. In order to identify comparable days for users, it is crucial to categorize the user's historical load curve beforehand [20].
3. Clustering Process, in this case number of cluster to be formed is 3.
4. Find pattern from the cluster result
5. Clustering validity in this research will be measured with DBI

IV. Result And Discussion

A. Data

The research utilizes data from social groups electricity users, collected over a period of one week with recordings taken every hour. Data collected for this social group is sourced from places of worship, educational institutions, and health services. The total data records used were 168 records for usage for 1 week for each type of social customer analyzed. Fig. 3 below is the process of obtaining data via AMR. Automatic Meter Reading (AMR) is typically connected with digital and smart meters [21]. In this work we use AMR to record data and send it to the system at the control centre.

Fig. 3. Process data transfer from AMR to control center

B. Preprocessing Data

Preprocessing is carry out by setting the data recording interval to every hour. If there is a missing value in the data, it is found using the median value function. However, if there is too much missing data, it will not be used in this research.

C. Clustering Process

To find the energy consumption patterns of social group customers in this research, a clustering process was carried out. The clustering process is carried out using the FCM algorithm. The number of clusters used in this research is 3. These 3 clusters can be categorized as low, medium and high energy use, the results of which are the matrix plots in Fig. 4.

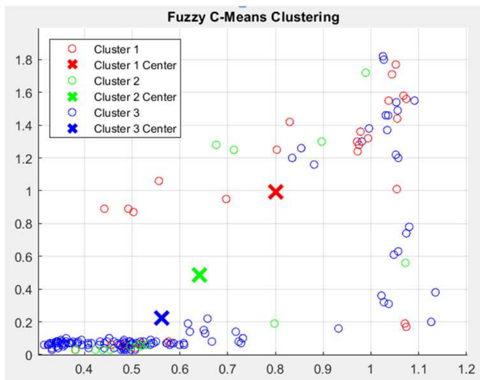

Fig. 4. Membership plot of matrix U

Cluster Centres:

$$\begin{bmatrix} 0.5 & 0.2 & 1.2 \\ 0.8 & 0.9 & 5.1 \\ 0.6 & 0.4 & 10.7 \end{bmatrix}$$

The number of clusters resulting from this research is 127 data records for the 1st cluster, 27 data records for the 2nd cluster and 13 data records for the 3rd cluster.

D. Energy Usage Pattern Social Customer

1) Health Services

Health services necessitate a consistent and substantial supply of electrical energy around the clock in order to operate a range of medical equipment, including lighting systems, HVAC (heating, ventilation, and air conditioning), and other technological devices. Analyzing energy consumption in health services can aid in the efficient planning and management of electricity usage, so maintaining a reliable power supply and reducing the likelihood of power failures. Fig. 4 illustrates a pattern where the consumption of electrical energy is generally higher on weekdays compared to other days, but it tends to be lower on weekends. This may occur due to the reduced operation hours or complete closure of health facilities, particularly outpatient clinics and doctor's offices, on weekends. Furthermore, the volume of patient visits often declines during weekends, with the exception of emergency situations. This can be a recommendation for health service facilities to schedule equipment maintenance and upkeep on weekends, especially in clusters of times when the operational load is lower as can be seen in Fig. 5 and 6.

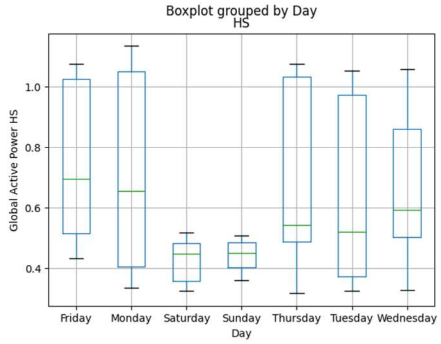

Fig. 5. Daily Health Services Energy Usage Pattern

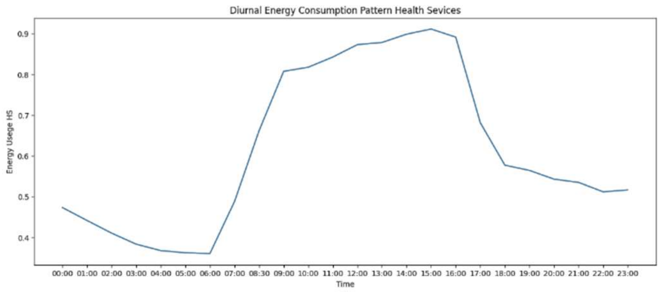

Fig. 6. Diurnal Health Services Energy Usage Pattern

The time group for low use of Electrical energy in health service facilities is from 00.00 to 06.00, the time group for medium use of Electrical energy is from 18.00 to 23.00, and the group for high use of Electrical energy is from 07.00 to 18.00.

2) Educational Institutions

Educational institutions are one type of electricity customer in the social group.

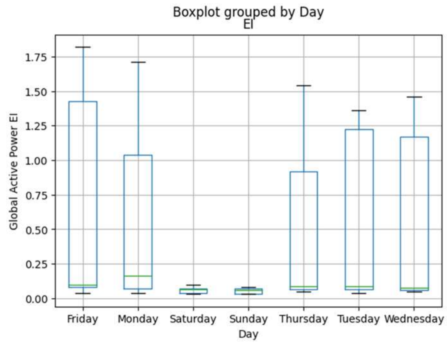

Fig. 7. Daily Educational Institutions Energy Usage Pattern

It can be seen in Fig. 7 and 8 that the pattern of electrical energy use in educational institutions tends to be stable on weekdays. On weekends, it appears that there are almost no operational activities that use electricity.

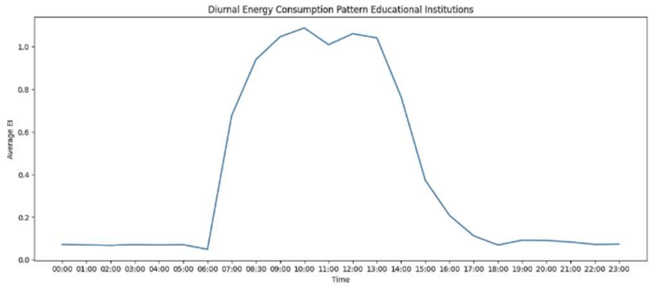

Fig. 8. Diurnal Educational Institutions Energy Usage Pattern

Fig. 7 shows the time cluster for electrical energy use in educational institutions. The time group included in the cluster of times with high use of electrical energy is in the time range 07.00 to 18.00. From 18.00 to 06.00 the next day the electricity usage tends to be smaller. Time between 18.00 to 06.00 in the same two clusters. Overlaps can appear in the Fuzzy C-Means (FCM) clustering technique due to the intrinsic fuzzy nature of this method. Data points can have membership in several clusters, resulting in overlap as can be seen from 18.00 to 06.00

3) Places of Worship

Places of worship in Indonesia generally have energy usage patterns that are unique and different from other social facilities, as shown in Fig. 9, where electrical energy usage can be high on certain days, for example, on weekends, holidays, and low on special days. other. Religious activities carried out in places of worship such as mosques, churches, temples, monasteries in Indonesia have special times related to their respective religious traditions and rituals. As can be seen in Fig. 9 and 10, electricity use is not always stable on certain days and at certain hours.

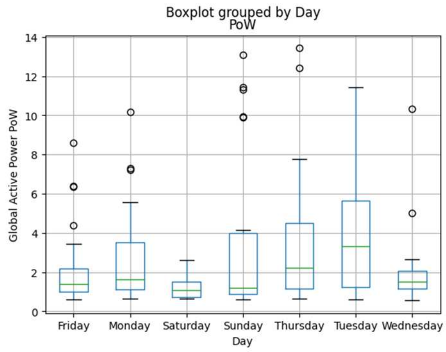

Fig. 9. Daily Places of Worship Energy Usage Pattern

In Fig. 9, there are outliers in the data, in this study we did not remove outliers, because in this case outliers in the data can also be additional important information that is useful because it can show the use of electrical energy on certain days for special purposes, for example in a places of worship used for weddings or other activities that cause a high spike in electrical energy use. Fig. 10 shows the time cluster for use of electrical energy in Places of Worship. The time group included in the high time cluster for electrical energy use is in the time range 07.00 to 10.00. 10.00 to 23.00 falls into the category of moderate use of electrical energy and at 00.00 and 06.00 the use of electrical energy tends to be smaller.

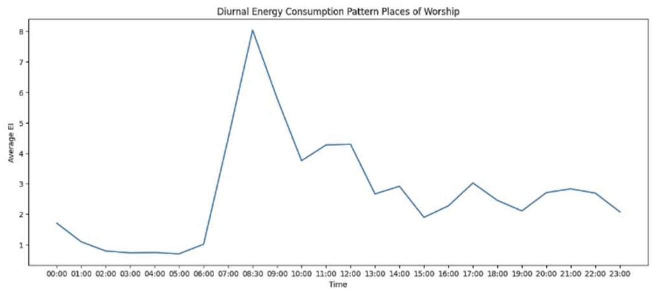

Fig. 10. Diurnal Places of Worship Energy Usage Pattern

The high time cluster shows high use of electrical energy for places of worship where religious rituals are carried out in the morning, the medium time cluster shows places of worship which are carried out in a time period where religious rituals can be carried out throughout the day at certain times and time groups Low indicates that there are almost no religious ritual activities carried out during these hours which require higher use of electrical energy.

E. Evaluate clustering quality

To measure the quality of cluster results in this research using the Davies-Bouldin index (DBI) method. The DBI value obtained in this study is 0.51. The score of 0.51 suggests that the resulting cluster is of high quality. Although not optimal, this value shows that the resulting clusters have good separation and a high level of homogeneity within the clusters.

V. IMPLICATION

The implication of this research is that by using the FCM method utility companies can identify more specific electrical energy use among social customers, such as Health Services, Educational Institutions, Places of Worship which of course have different energy use characteristics. Apart from that, this analysis can also help utility companies design business strategies, operations, planning and energy policies that can be tailored to each group.

Based on the experimental results, utility companies can improve planning and management of network infrastructure for places of worship, educational institutions and health services by allocating more resources during peak consumption times or implementing smart grid technology to manage loads dynamically. This can increase operational efficiency, reduce the risk of overload, and optimize network capacity which can predict consumption spikes and avoid blackouts by adjusting load distribution on places of worship, educational institutions, and health services by allocating additional resources during peak load times. Apart from that, it is also possible to develop an FCM-based energy management system from this research which is integrated with a SCADA system for real time monitoring and control.

VI. CONCLUTION

The research findings indicate that applying FCM with cluster quality measurement results with a DBI of 0.51 to group the time of electrical energy use in social customer segments, specifically in Health Services, Educational Institutions, and Places of Worship, can provide a comprehensive understanding of energy that shows energy use patterns for different types of electricity even though they are included in the same electricity tariff category. This understanding is derived from analyzing distinct energy usage patterns, enabling the formulation of tailored strategy recommendations for each customer type. In addition, this research can assist power companies in formulating tariffs that align better with the energy consumption patterns of social users, such as implementing specific prices for particular time periods or offering incentives for energy usage during non-peak hours.

VII. FURTHER RESEARCH SUGGESTIONS

Based on the cases that have been conducted in this research with FCM, further research can be considered to investigate the application of intelligent technology that can aid in the planning of energy management and the management of electricity load for each category of electricity customer group based on the time of use.

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