K-Means Clustering of Electricity Consumption from IoT Data: A Case Study in Electrical Engineering Department Building, ITN Malang

Irrine Budi Sulistiawati
Department of Electriccal Engineering
National Institute of Technology (ITN) Malang
Malang, Indonesia
irrine@lecturer.itn.ac.id

Aryuanto Soetedjo
Department of Electriccal Engineering
National Institute of Technology (ITN) Malang
Malang, Indonesia
aryuanto@lecturer.itn.ac.id

F. Yudi Limpraptono
Department of Electriccal Engineering
National Institute of Technology (ITN) Malang
Malang, Indonesia
fyudil@lecturer.itn.ac.id

Sugeng Priyanto
Department of Electrical Engineering
National Institute of Technology (ITN) Malang
Malang, Indonesia
PT. YTL, East Java,
Indonesia

2023 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT) | 979-8-3503-4110-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/COMNETSAT59769.2023.10420576

***Abstract*— The electricity consumption profile represents the occupant's behavior in consuming electricity. It provides valuable information in the energy management system. This paper presents a work for clustering electricity consumption using the K-means clustering technique. Instead of a whole building, our approach deals with grouping the electricity consumption in each room, namely the Automation Laboratory and Department Office of the Electrical Engineering Department of ITN Malang. The electricity dataset is obtained from the IoT data of the Building Automation System (BAS) installed in the rooms, which records each room's lamps and outlet consumption separately. The clustering results show that individual rooms' load profile provides a more detailed profile than the aggregated ones. Further, the developed IoT-based BAS system offers a valuable approach to electricity consumption clustering.**

Keywords*— Electricity consumption, IoT, K-means clustering, Load profile;

I. INTRODUCTION

Electricity consumption clustering is a method to group the electricity consumption data according to a similar pattern. It can be applied to consumer segmentation, implementation of tariff policy, load anomaly detection, load forecasting, and demand side management [1]. The electricity clustering can be used for consumer segmentation based on the peak demand profiles [2]. Based on the load profiles, the policymaker can design the demand response for maintaining the power system stability and the different time of use tariffs [3]. The anomaly detection of energy consumption can be used to improve energy saving [4]. Even though the common method for load prediction uses the electricity consumption of a building [5],[6], the energy consumption prediction based on each group from the clustering technique may improve the prediction performance [7]. Load prediction can also be developed based on combining the energy consumption pattern and user behavior model [8].

Five major clustering techniques used for electricity consumption clustering are [9]: K-means, fuzzy c-mean, hierarchical, self-organizing map (SOM), and model-based approach. The K-means clustering is the most popular among them.

The application of electricity consumption clustering can be divided into residential buildings [3],[10]–[19] and non-residential buildings [19]–[23]. In [10], a load estimation was developed based on K-means clustering, where the data were collected from the smart metering of domestic consumers. In [11], electricity consumption at home was analyzed using K-means clustering from the University of California Irvine Machine Learning Dataset Repository [24]. Six load patterns of residential houses: energy consumption in the morning, energy saving in the morning, M-pattern (similar energy consumption in the morning and evening), morning concentrated energy consumption, evening concentrated energy consumption, and large energy consumption at daybreak, were found by K-means clustering [12].

In [16], K-means clustering was used to group the household consumption obtained from the London Data Store energy consumption dataset. It found three clusters, where two had a similar pattern of low consumption in the morning, then increased in the afternoon and evening, and the third cluster had the highest consumption in all periods. In [17], at first, K-means was used to find a similar pattern of load consumption, and then deep learning was used to forecast the load consumption in each resident. The work in [18] concluded that load forecasting based on clustering was better than without clustering.

In [19], K-means clustering was used to group the electricity consumption in the residential and commercial buildings. The dataset was obtained from the Meter Reader Billing Statement System of Sultan Kudarat Electric Cooperative, Inc. (SUKELCO), Philippines. The Elbow method was employed to find the best number of clusters. The three clusters were found to be the best number of clusters for residential and commercial electricity consumption. The three clusters were the low, medium, and high average electricity consumption.

In [20], K-means clustering was used to group the electricity consumption in three different buildings of Chubu University: science, non-science, and office buildings. Then the energy consumption was analyzed based on human activities and air-conditioning. A method to select the better initial centroids was proposed in [21] to improve the K-means performance. In [22], the load profiles of Kimmeria Campus of Democritus University of Thrace was analysed using K-means++ clustering. Several clustering techniques such as K-means, K-shape, partition around medoid, and hierarchical agglomerative algorithms were compared to cluster the electricity load of the buildings [23]. The experimental results showed that K-means clustering achieved the best performance.

Most works described previously deal with the electricity consumption clustering of residential and non-residential buildings, where the load data are collected from the smart metering. In this paper, instead of a whole building, we deal with the clustering of electricity consumption in the rooms of a building. More specifically, in the laboratory and department office rooms of the Electrical Engineering Department, National Institute of Technology (ITN) Malang, Indonesia. To the best of our knowledge, there is no such work dealing with load clustering in the rooms of a building. The availability of Internet of Things (IoT) data on electricity consumption in the department building room supports our approach effectively.

The main objectives of our work are conducting the energy consumption clustering at a micro level, i.e., based on the energy consumption of the rooms at the university building. More detailed information can be obtained by clustering and analyzing the load profile of each room. Thanks to the IoT technology that provides the electricity consumption data of each room. Further, this approach can be incorporated with the embedded Artificial Intelligent (AI) for better energy management in the building.

The rest of paper is organized as follows. Section 2 describes the methodology of our work. Section 3 presents the result and discussions. Finally, conclusion is covered in Section 4.

II. Methodology

A. Overview of Building Automation System using IoT in Electrical Engineering Department Building

The Building Automation System (BAS) in the Electrical Engineering Department Building of the National Institute of Technology Malang was developed in 2005, and several rooms were upgraded using IoT technology in early 2023. Currently, the upgraded IoT-based BAS comprises of the Postgraduate Department, Automation Laboratory, Robotics, Undergraduate Department Head, Secretary, and Administration rooms. The architecture of the IoT system for measuring electricity consumption is depicted in Fig. 1. In this work, for simplicity, we only consider the electricity consumption in the Automation Laboratory and Department Office rooms. As shown in the figure, the PZEM-004T low-cost power sensor is used to measure the power consumption of the lamp and outlet. Since the PZEM-004T has the Modbus RTU protocol, a Modbus RTU to WiFi converter (Elfin-EW11) is employed to convert the Modbus RTU to Modbus TCP, which is transmitted via WiFi communication.

The Haiwell IoT Cloud HMI is the master unit that requests the data from the power sensors, displays, and stores the data on the memory. Then the data can be exported to a CSV file for further analysis. The dashboard of IoT-based BAS is illustrated in Fig. 2, where the current implementation system is shown in the right part. The Haiwell IoT Cloud HMI is connected to the cloud server;

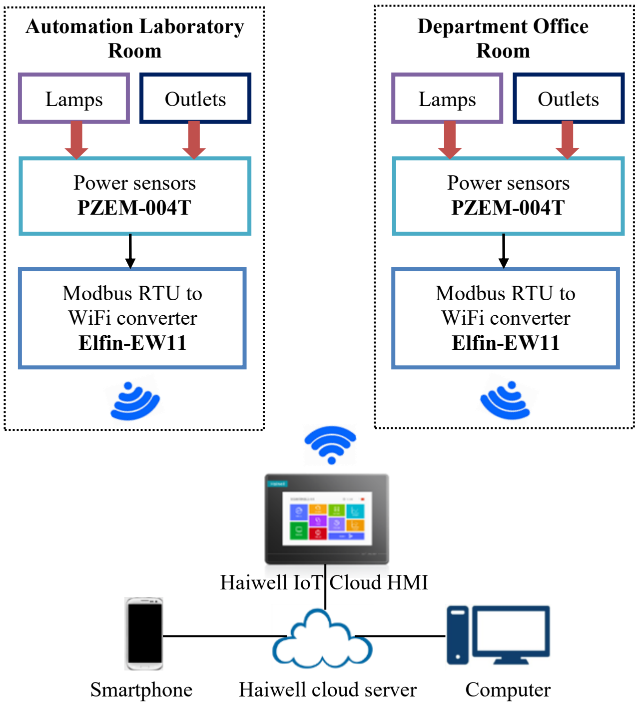

Fig. 1. Architecture of IoT-based electricity consumption measurement.

thus, the dashboard can be accessed using a web browser on a computer or an Android application on a smartphone.

B. Electrical Consumption Clustering using K-means Algorithm

K-means clustering is a popular algorithm for grouping data into a defined number of clusters. The algorithm is as follows [10][17]:

1. Specify the number of clusters *K*,
2. Initialize the *K* cluster centers randomly,
3. Assign each data to the closed cluster center using the following formula:

$$\forall i = 1,2,\ldots,n : c_{ik} = \begin{cases} 1 & k = \arg\min_j \left\| x_i - \mu_j \right\|_2^2 \\ 0 & otherwise \end{cases} \tag{1}$$

   where n is the number of dataset; k=1,2,…,K; x_i is the i^{th} data sample; μ_j is the cluster center of j^{th} cluster,

4. Update each cluster center using the following formula:

$$\forall k = 1,2,\ldots,K : \mu_k = \frac{1}{m_k} \sum_{i \in S_k} x_i \tag{2}$$

   where S_k is set of data samples which are assigned to k^{th} cluster; m_k is the number of data samples in S_k,

5. Repeat Step-3 to Step-4 until no cluster members are assigned to the new clusters.

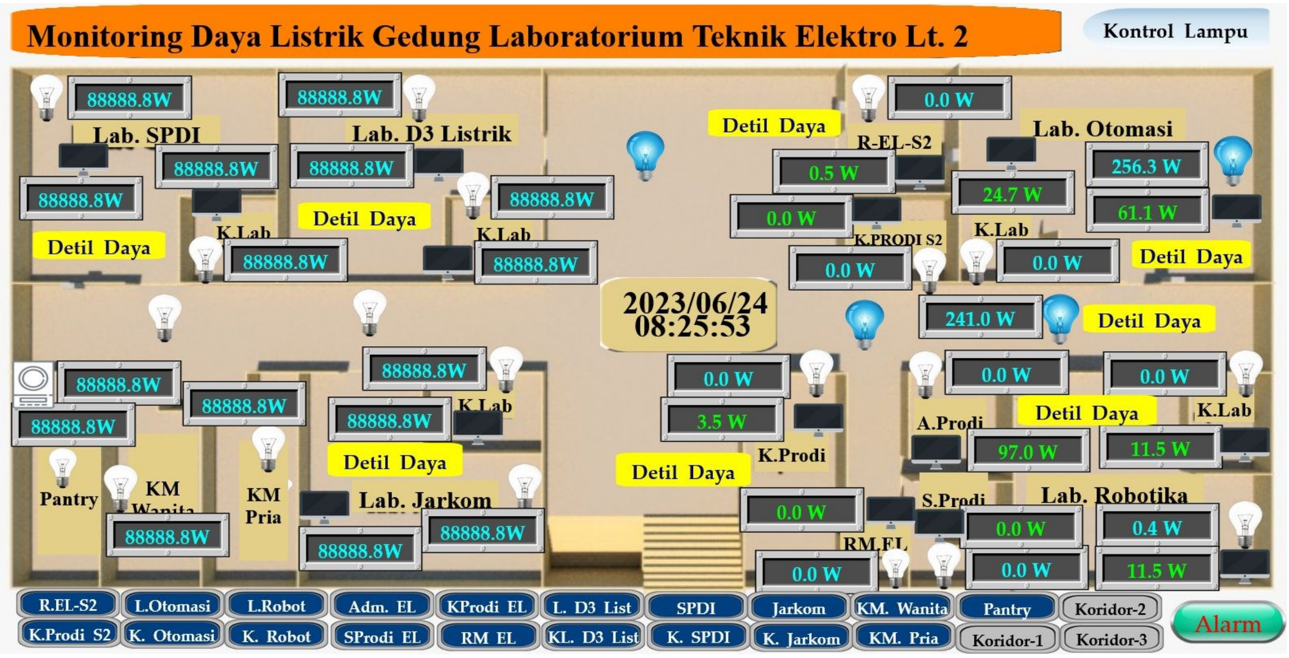

Fig. 2. Dashboard of IoT-based BAS.

In this work, K-means clustering is used to find a daily profile of electricity consumption in the rooms, namely the laboratory and department office rooms. These rooms are selected due to their different characteristics as follows. The laboratory room has two main activities: the laboratory head activity and the laboratory assistant activity. Meanwhile, the department room comprises the department head, secretary, and administration staff with the same activity time.

The K-means clustering is implemented on a Python language using *sci-kit learn* [25], a machine learning library for Python. Further, the *Matplotlib* library is used for visualization the dataset and clustering results.

C. *Electricity Consumption Data Collection*

In this work, we used the dataset from the IoT data described previously. The data is recorded from 25/5/2023 to 2/7/2023 with a time interval of 5 minutes. The data structure is listed in Table I. In the Automation Laboratory, the lamp power consumption comprises the consumption of lamps in the head of the laboratory room and experiments and laboratory assistant rooms. The outlet power consumption comprises personal computers, a printer, an LCD projector, and laboratory instruments. In the Department Office, the lamp power consumption comprises the consumption of lamps in the head of the department room, the secretary of the department room, and the administration staff of the department room.

TABLE I. DATA STRUCTURE

No	Room Name	Data			
1.	Automation Laboratory	Timestamp	Lamp Power	Outlet Power	Total Power
2.	Department Office	Timestamp	Lamp Power	Outlet Power	Total Power
3	Automation Laboratory and Department Office	Timestamp	Lamp Power	Outlet Power	Total Power

The outlet power consumption comprises personal computers, printers, LCD projectors, a refrigerator, and a water heater (coffee maker).

III. RESULT AND DISCUSSIONS

The K-Means clustering technique requires a pre-defined number of clusters. In this work, we find the optimal number of clusters by selecting the best number from the numbers obtained by the elbow method of the silhouette scores and inertia. Fig. 3 and Fig. 4 show the silhouette scores and inertia of the lamp consumption profiles in the Automation Laboratory room, respectively. The number of clusters of the elbow methods and the selected ones are listed in Table II. Table II shows that most clusters' numbers obtained by the silhouette and inertia method are the same. In the cases of different numbers, we select the lowest one, representing the more realistic pattern.

The K-means clustering results of the datasets described in Section 2 are depicted in Figs. 5 to 13. The figures plot daily electricity consumption profiles from 00:00 h to 23:00 h.

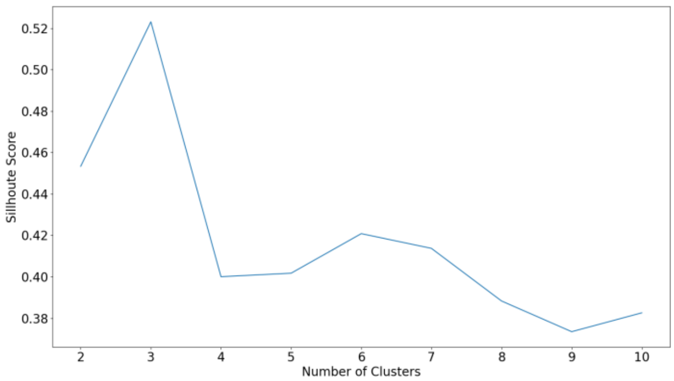

Fig. 3. The number of clusters using silhoutte score of the lamp consumption profiles in the Automation Laboratory room.

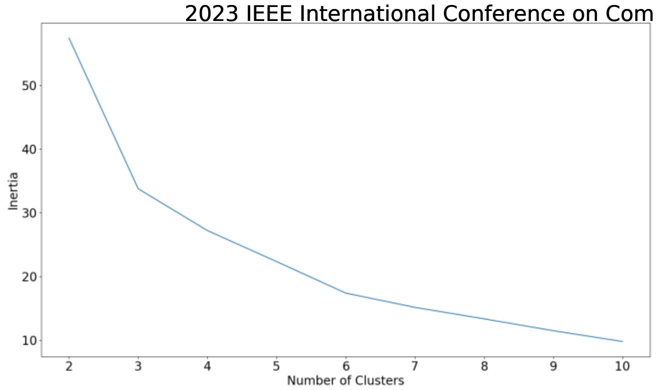

Fig. 4. The number of clusters using inertia of the lamp consumption profiles in the Automation Laboratory room .

In the figures, thin solid lines represent the raw load data, while the tick dashed lines are the profiles of the K-means clustering results. It is worth noting that in each figure, the number of clusters is given in Table II.

In order to have a better understanding for analyzing the load profile, some characteristics of the building rooms and occupant behaviors are observed as follows:

1. The lamp in the room should be turned on when the occupant stays there, regardless the time (daytime or nighttime),
2. There is no occupancy sensor yet. Thus in some conditions, the lamp is not turned off when the occupant leaves the room,
3. In a particular condition, overtime occurs at night or during Saturday and Sunday,
4. Several loads, such as network switch, BAS control unit, and refrigerator, are always turned on.

Fig. 5, 6, and 7 illustrate the electricity consumption profiles of the lamp, outlet, and total lamp and outlet in the Automation Laboratory room, respectively. Fig. 5 shows three clusters of the lamp consumption profiles in the Automation Laboratory. The first cluster is the profile with zero power during the whole day. It happens during holidays (Saturday and Sunday), with no Laboratory activities. The second cluster is the profile when the lamp power increases in the morning and decreases in the afternoon. Number of Clusters

TABLE II. NUMBER OF CLUSTERS

No	Load Profile	Number of Clusters		
		Elbow Method		Selected
		Silhouette	Inertia	
1.	Automation Laboratory - Lamp	3	3	3
2.	Automation Laboratory - Outlet	6	4	4
3.	Automation Laboratory - Lamp and Outlet	3	3	3
4.	Department Office - Lamp	7	3	3
5.	Department Office - Outlet	3	3	3
6.	Department Office - Lamp and Outlet	6	4	4
7.	Automation Laboratory and Department Office - Lamp	3	3	3
8.	Automation Laboratory and Department Office - Outlet	5	4	4
9.	Automation Laboratory and Department Office - Lamp and Outlet	3	3	3

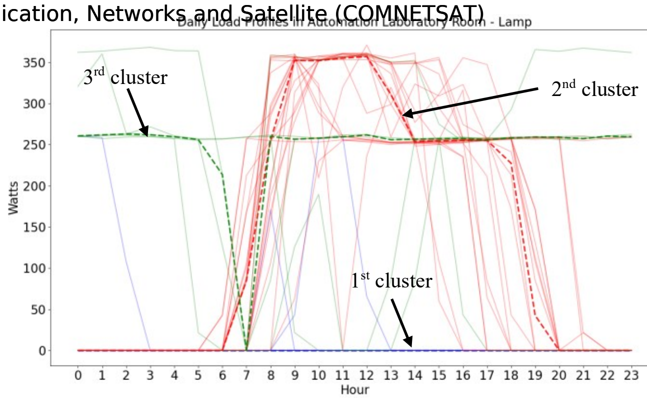

Fig. 5. Lamp consumption profiles in Automation Laboratory room.

It represents the electricity consumption on regular working days. The third cluster is the profile when there is an overtime activity during the holiday, and the laboratory assistants leave the room in the early morning.

Fig. 6 shows four clusters of the outlet consumption profiles in the Automation Laboratory. The first cluster is the profile with low power consumption throughout the day. It is consumed by the network switch and BAS control unit. The second and third clusters are the profiles when the outlet powers increase in the morning and decrease in the afternoon. In the second cluster, the laboratory activity in the afternoon (15:00 h) produces the peak consumption. The third cluster shows the overtime work at night. The fourth cluster is the profile when there is an overtime activity, where the laboratory assistants stay in the room at night.

Fig. 7 shows three clusters of the lamp and outlet consumption profiles in the Automation Laboratory. It is similar to Fig. 5 (lamp profile). This result shows that lamp consumption dominates the daily load profile.

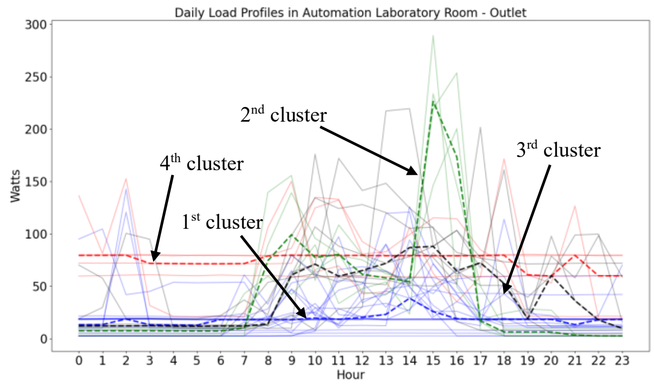

Fig. 6. Outlet consumption profiles in Automation Laboratory room.

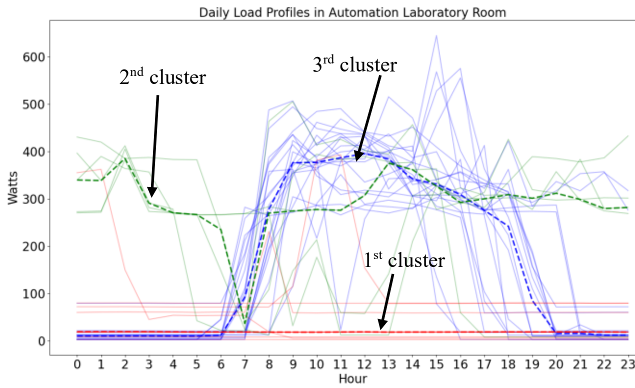

Fig. 7. Lamp and outlet consumption profiles in Automation Laboratory room.

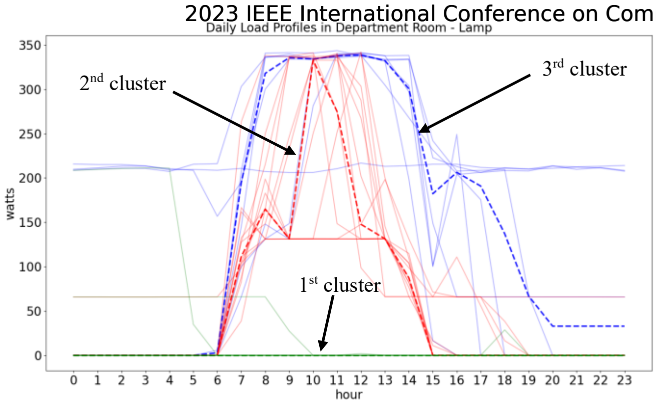

Fig. 8. Lamp consumption profiles in Department Office room.

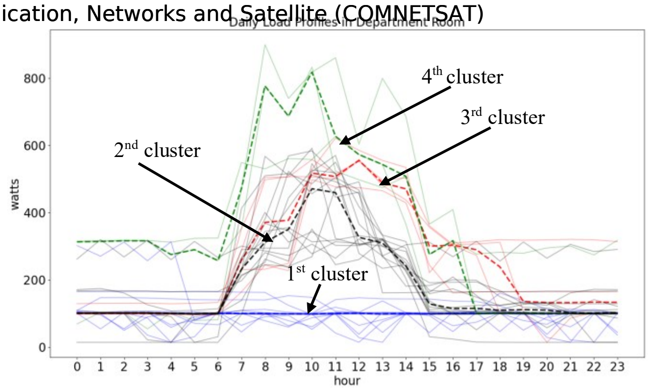

Fig. 10. Lamp and outlet consumption profiles in Department Office room.

Fig. 8, 9, and 10 illustrate the electricity consumption profiles of the lamp, outlet, and total lamp and outlet in the Department Office room, respectively. Fig. 8 shows three clusters of the lamp consumption profiles. The first cluster is similar to the Automation Laboratory room, i.e., the profile has zero power during the whole day on Saturday and Sunday. The second and third clusters represent the low and high load profiles, respectively. The department staff do not stay in their rooms simultaneously in the low load profile. For instance, when the head and secretary of the department go out for a meeting or teaching. In the high load profile, all department staff have the activities in their rooms.

Fig. 9 shows three clusters of the outlet consumption profiles in the Department Office. The first cluster is the refrigerator power consumption profile, which consumed the whole day, including Saturday and Sunday. The second cluster is the load profile of the regular activity in the working days, such as using personal computers, a scanner, and printers. The third cluster represents the load profile of using the coffee maker and LCD projectors.

Fig. 10 shows four clusters of the lamp and outlet consumption profiles in the Department Office. The first cluster corresponds to the first cluster in Fig. 9, i.e., the load profile of the whole day load. The second and third clusters are almost similar in terms of the amount of power consumption. They differ in the time usage, where the second cluster corresponds to the second cluster in Fig. 8, and the third cluster corresponds to the third cluster in Fig. 8. The fourth cluster corresponds to the high consumption of the third cluster in Fig. 8.

Figs. 11, 12, and 13 illustrate the electricity consumption profiles of the lamp, outlet, and total lamp and outlet in the Automation Laboratory and Department Office rooms, respectively.

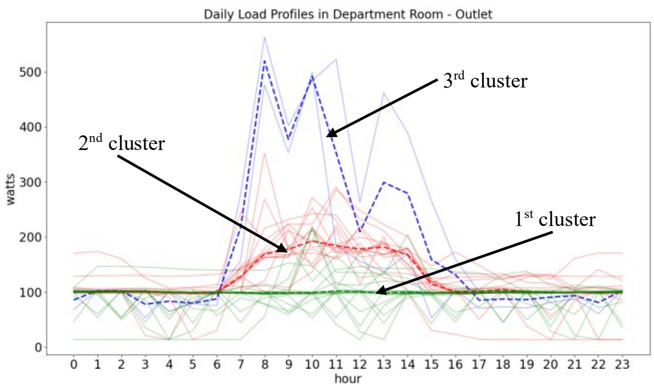

Fig. 9. Outlet consumption profiles in Department Office room.

Fig. 11 shows three clusters of the lamp consumption profiles. The first cluster corresponds with the first cluster in Figs. 5 and 8, representing zero power during the holidays. The second cluster corresponds with the third cluster in Fig. 5, which represents the overtime activity in the Automation Laboratory. The third cluster represents the load profile of the regular activities in the Automation Laboratory and Department Staff rooms.

Fig. 12 shows four clusters of outlet consumption profiles in the Automation Laboratory and Department Office rooms. The first cluster represents the whole day's power consumption profile, such as a refrigerator, network switches, and BAS control unit. The second and third clusters correspond with the combination of regular power consumption in the Automation Laboratory and Department Office, where the second cluster represents the overtime activity at night. The fourth cluster corresponds with the third cluster in Fig. 9, representing the coffee maker's and LCD projectors' usage.

Fig. 13 shows three clusters of the lamp and outlet consumption profiles in the Department Office. The first cluster corresponds to the first cluster in Fig. 12. The second cluster corresponds with the load profile during overtime activities. The third cluster represents the profile of the regular activities.

From the above discussions, we have several findings as follows:

1. By clustering the lamp and outlet power consumptions in each room separately, we get more valuable information about the load profiles in detail,
2. Due to the different behavior of the occupants' activities, clustering the load profile in each room provides a better understanding of the electricity consumption,

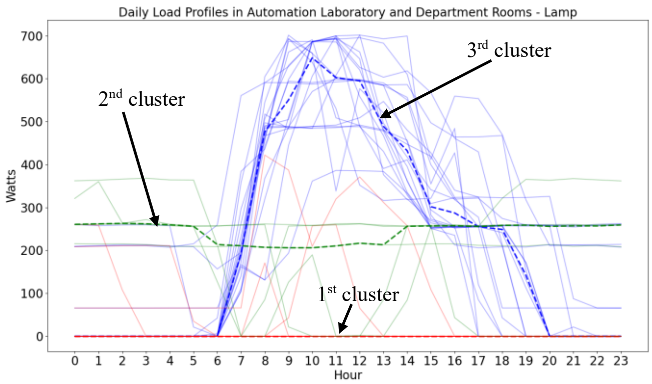

Fig. 11. Lamp consumption profiles in Automation Laboratory and Department Office rooms.

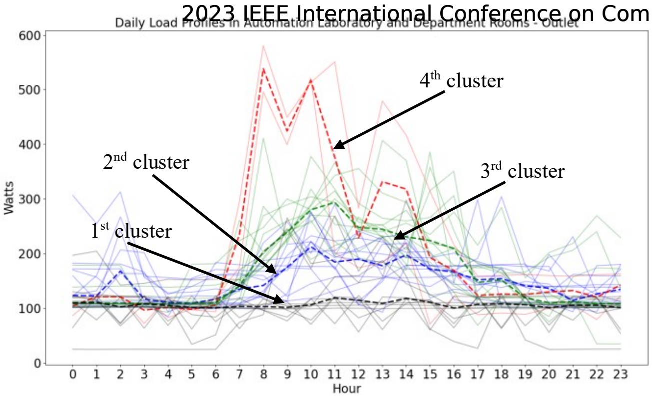

Fig. 12. Outlet consumption profiles in Automation Laboratory and Department Office rooms.

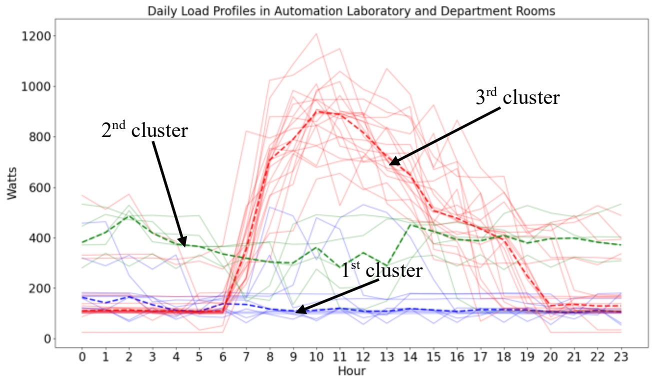

Fig. 13. Lamp and outlet consumption profiles in Automation Laboratory and Department Office rooms.

3. The optimal cluster numbers obtained in the aggregated loads (e.g., aggregation of the lamp and outlet or aggregation of the Automation Laboratory and Department Office) are lower than the individual ones. It suggests that several profiles cannot be clustered in the aggregated loads.

Table III compares our method to the existing systems, especially those that use K-means to cluster electricity consumption in commercial or university buildings. The table shows that our proposed approach provides several benefits, such as dealing with the detailed analysis of energy consumption in each room of a university building and adopting IoT technology to support the dataset.

TABLE III. COMPARISON TO EXISTING SYSTEMS

Ref.	Clustering scope	Dataset	Cluster analysis
[19]	Commercial buildings in a province	Meter reading billing – Electric company	Average electricity consumption of buildings
[20], [21]	University buildings	Energy consumption sensors in the buildings	Energy pattern in three different buildings in the university
[26]	University buildings	Smart metering systems	Electricity consumption of the campus
[23]	Telecommunication company buildings	Smart meter	Grouping according the building usage categories
Proposed	University building	IoT-based Building Automation System	Energy pattern in each room in the university building

IV. CONCLUSION

The electricity consumption in the Automation Laboratory and Department Office of Electrical Engineering ITN Malang was clustered using the K-means clustering, where the IoT-based Building Automation System provided the dataset. The load profiles of individual consumptions of the lamps, outlets, and the room were investigated and compared to the aggregation ones. The results suggested that the load profiles of the aggregation approach did not reflect the occupants' behavior in detail. In the future, the work will be extended to cover the larger areas. Further, the sophisticated clustering technique and related algorithms will be investigated.

ACKNOWLEDGMENT

This work is supported by the research grant from the Institute for Research and Community Service ITN Malang and the Building Automation System (BAS) Project of ITN Malang, Year 2023.

REFERENCES

[1] C. Si, S. Xu, C. Wan, D. Chen, W. Cui, and J. Zhao, “Electric Load Clustering in Smart Grid: Methodologies, Applications, and Future Trends,” Journal of Modern Power Systems and Clean Energy, vol. 9, no. 2, pp. 237–252, 2021, doi: 10.35833/MPCE.2020.000472.

[2] R. Kaur and D. Gabrijelčič, “Behavior segmentation of electricity consumption patterns: A cluster analytical approach,” Knowledge-Based Systems, vol. 251, 2022, doi: 10.1016/j.knosys.2022.109236.

[3] S. Cen, J. H. Yoo, and C. G. Lim, “Electricity Pattern Analysis by Clustering Domestic Load Profiles Using Discrete Wavelet Transform,” Energies, vol. 15, no. 4, 2022, doi: 10.3390/en15041350.

[4] L. Lei, B. Wu, X. Fang, L. Chen, H. Wu, and W. Liu, “A dynamic anomaly detection method of building energy consumption based on data mining technology,” Energy, vol. 263, no. August 2022, 2023, doi: 10.1016/j.energy.2022.125575.

[5] Q. Wei, Q. Li, Y. Yang, L. Zhang, and W. Xie, “A summary of the research on building load forecasting model of colleges and universities in North China based on energy consumption behavior: A case in North China,” Energy Reports, vol. 8, pp. 1446–1462, 2022, doi: 10.1016/j.egyr.2022.02.009.

[6] R. Lei and J. Yin, “Prediction method of energy consumption for high building based on LMBP neural network,” Energy Reports, vol. 8, pp. 1236–1248, 2022, doi: 10.1016/j.egyr.2022.02.071.

[7] N. A. Dao, H. M. Nguyen, and K. T. Nguyen, “Mining for Building Energy-consumption Patterns by using Intelligent Clustering,” IEIE Transactions on Smart Processing and Computing, vol. 10, no. 6, pp. 469–476, 2021, doi: 10.5573/IEIESPC.2021.10.6.469.

[8] F. Lazzari et al., “User behaviour models to forecast electricity consumption of residential customers based on smart metering data,” Energy Reports, vol. 8, pp. 3680–3691, 2022, doi: 10.1016/j.egyr.2022.02.260.

[9] A. Rajabi, M. Eskandari, M. J. Ghadi, L. Li, J. Zhang, and P. Siano, “A comparative study of clustering techniques for electrical load pattern segmentation,” Renewable and Sustainable Energy Reviews, vol. 120, no. November, 2020, doi: 10.1016/j.rser.2019.109628.

[10] A. Al-Wakeel, J. Wu, and N. Jenkins, “K-Means Based Load Estimation of Domestic Smart Meter Measurements,” Applied Energy, vol. 194, pp. 333–342, 2017, doi: 10.1016/j.apenergy.2016.06.046.

[11] H. W. Choi, N. M. F. Qureshi, and D. R. Shin, “Analysis of Electricity Consumption at Home Using K-means Clustering Algorithm,” International Conference on Advanced Communication Technology, ICACT, vol. 2019-Febru, no. February, pp. 639–643, 2019, doi: 10.23919/ICACT.2019.8701981.

[12] H. C. Jeong, M. Jang, T. Kim, and S. K. Joo, “Clustering of load profiles of residential customers using extreme points and demographic characteristics,” Electronics (Switzerland), vol. 10, no. 3, pp. 1–10, 2021, doi: 10.3390/electronics10030290.

[13] A. Tureczek, P. S. Nielsen, and H. Madsen, “Electricity consumption clustering using smart meter data,” Energies, vol. 11, no. 4, pp. 1–18, 2018, doi: 10.3390/en11040859.

[14] Z. Zhang and T. Zimet, “K-means Based Clustering Analysis of Household Energy Consumption,” no. December, 2018.

[15] A. Al-Wakeel and J. Wu, "K-means based cluster analysis of residential smart meter measurements," Energy Procedia, vol. 88, pp. 754–760, 2016, doi: 10.1016/j.egypro.2016.06.066.

[16] G. E. Okereke, M. C. Bali, C. N. Okwueze, E. C. Ukekwe, S. C. Echezona, and C. I. Ugwu, "K-means clustering of electricity consumers using time-domain features from smart meter data," Journal of Electrical Systems and Information Technology, vol. 10, no. 1, 2023, doi: 10.1186/s43067-023-00068-3.

[17] F. Han, T. Pu, M. Li, and G. Taylor, "Short-Term forecasting of individual residential load based on deep learning and K-means clustering," CSEE Journal of Power and Energy Systems, vol. 7, no. 2, pp. 261–269, 2021, doi: 10.17775/CSEEJPES.2020.04060.

[18] H. Kim, S. Park, and S. Kim, "Time-series clustering and forecasting household electricity demand using smart meter data," Energy Reports, vol. 9, pp. 4111–4121, 2023, doi: 10.1016/j.egyr.2023.03.042.

[19] E. Bagundang and C. Rael, "Clustering Commercial And Residential Electricity Consumption Using K-Means Algorithm," vol. 10, no. 08, pp. 8–11, 2021.

[20] B. Nepal, M. Yamaha, and H. Sahashi, "Energy conservation in university buildings by energy pattern analysis using clustering technique," *International Journal of Energy Production and Management*, vol. 4, no. 2, pp. 158–167, 2019, doi: 10.2495/EQ-V4-N2-158-167.

[21] B. Nepal, M. Yamaha, H. Sahashi, and A. Yokoe, "Analysis of building electricity use pattern using k-means clustering algorithm by determination of better initial centroids and number of clusters," Energies, vol. 12, no. 12, 2019, doi: 10.3390/en12122451.

[22] A. G. Kazaki and T. A. Papadopoulos, "Cluster analysis of university campus smart meter data," Proceedings - 2018 53rd International Universities Power Engineering Conference, UPEC 2018, pp. 1–6, 2018, doi: 10.1109/UPEC.2018.8541941.

[23] S. Eiraudo et al., "A Machine Learning Based Methodology for Load Profiles Clustering and Non-Residential Buildings Benchmarking," IEEE Transactions on Industry Applications, vol. 59, no. 3, pp. 2963–2973, 2023.

[24] "Individual household electric power consumption." [Online]. Available: https://archive.ics.uci.edu/dataset/235/individual+household+electric+power+consumption

[25] F. Pedregosa and et al, "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

[26] A. G. Kazaki and T. A. Papadopoulos, "Cluster analysis of university campus smart meter data," *Proceedings - 2018 53rd International Universities Power Engineering Conference, UPEC 2018*, pp. 1–6, 2018, doi: 10.1109/UPEC.2018.8541941.