©2025 Published in 11th International Symposium on Intelligent Technologies in Engineering and Science 16-18 May 2025 (ISITES2025 Diyarbakır - Turkey)

Development of an IoT-Based Energy Monitoring System and Analysis of Energy Consumption Behaviors: A Faculty Building Application

*[1]Kadir Doğanşahin and [1]Ali Yüce
*[1]Department of Electrical and Electronics Engineering, College of Engineering and Natural Sciences, Malatya Turgut Ozal University, Malatya, Turkey

Abstract

A low-cost IoT-based monitoring system has been developed to collect and analyze energy data from the main electrical distribution panel of the College of Engineering and Natural Sciences (CENS) building at Malatya Turgut Özal University. Within the scope of the study, energy consumption profiles of the college building have been analyzed based on the collected data. Using the developed energy monitoring device, three-phase voltage, current, active power, reactive power, and energy consumption data have been read from the energy analyzer device at one-minute resolution, transferred via the RS485 communication protocol and stored on a server. In this paper, daily consumption profiles have been created with hourly resolution based on the data collected between February 3 and April 20, 2025, corresponding to the Spring semester of the 2024–2025 academic year. Using k-means clustering algorithm, daily consumption profiles have been segmented, and three different consumption patterns have been identified. Upon examining these consumption patterns, usage intensity-related consumption patterns of the building have been revealed and interpreted. As the result, the findings demonstrate that implementing IoT-based energy monitoring systems in higher education buildings significantly contributes to revealing detailed energy consumption characteristics and, consequently, to the development of effective energy efficiency strategies.

Key words: IoT-Based Energy Monitoring, K-Means Clustering, Energy Consumption Behavior, Smart Campus Applications

1. Introduction

The efficient use of energy resources has become a significant field of research and application worldwide due to increasing energy demand, economic concerns, and environmental issues [1]. In particular, accurate monitoring and analysis of energy consumption in university campuses—which typically consist of large-scale buildings and host dense user traffic—are critically important both for reducing costs and achieving sustainability goals [2].

Traditional energy monitoring and management systems often suffer from drawbacks such as high installation costs, limited flexibility, and insufficient real-time data capabilities [3]. In recent years, solutions developed using Internet of Things (IoT) technologies have gained prominence due to their low cost, scalability, and ability to collect real-time data. IoT-based energy monitoring systems enable detailed analysis of consumption behaviors by providing a continuous flow of data from numerous sensors and devices [4-5].

Research in this area has shown that monitoring energy parameters using IoT devices in university

*Corresponding author: Address: Department of Electrical and Electronics Engineering, College of Engineering and Natural Sciences, Malatya Turgut Ozal University, Malatya TURKEY. E-mail address: kadir.dogansahin@ozal.edu.tr, Phone: +90422 846 1255

buildings is effective for both real-time condition detection and identifying long-term consumption trends. For instance, in a study conducted by Zhu et al., IoT sensor data collected over two years from 18 educational buildings in Greece, Italy, and Sweden have been analyzed. The study states that these analyses have the potential to provide building managers with valuable information on reducing energy consumption. [6]. In the GAIA project led by Mylonas et al., up to 20% energy savings have been achieved through the IoT infrastructure installed in school buildings, demonstrating the potential of IoT for promoting energy savings in educational settings [7].

Moreover, machine learning techniques and statistical analysis methods are increasingly used to extract meaningful insights from large volumes of energy data. In particular, clustering techniques offer an effective approach for classifying and characterizing energy consumption profiles [8-9]. Segmenting the consumption patterns of a campus on various days can provide significant benefits for operational planning and anomaly detection.

In this study, energy consumption data have been collected from an energy analyzer device with the RS485 communication protocol installed in the main electrical distribution panel of a building located at Malatya Turgut Özal University's Yeşilyurt Campus. Using the developed IoT-based system, the data has been recorded on a server with one-minute resolution. After various data preprocessing, the collected data have been converted to daily energy consumption profiles with one-hour resolution, which have then been segmented by using the k-means clustering algorithm. The results demonstrate that the low-cost IoT-based system has high potential for creating energy management and optimization strategies at the campus scale.

The following pages contain the material and method section, which provides information about the hardware of the developed device and the methods used within the scope of the study. The presentation and interpretation of the results obtained have been implemented under the title of Results and Discussion. The last part of the study includes a section summarizing the remarkable findings obtained within the study.

2. Materials and Methods

2.1. Hardware and Data Collection Structure

A low-cost and flexible IoT-based system has been developed to monitor the energy consumption data of the building of the College of Engineering and Natural Sciences (CENS) located on the Yeşilyurt Campus of Malatya Turgut Özal University. The energy monitoring system consists of three main parts, energy analyzer device, developed data acquisition board and web interface.
Energy analyzers installed in the building's electrical distribution panels are devices capable of measuring various energy parameters, primarily including three-phase voltage, current, active power, reactive power, and total energy consumption. The analyzer used in the main electrical distribution panel of the CENS building communicates via the RS485 communication line using the Modbus RTU protocol. This communication standard ensures reliability and is suitable for long-distance data transmission.

The data retrieved from the energy analyzer is transmitted to the Wi-Fi network through a developed data acquisition board. The developed board offers advantages over commercial alternatives thanks to its low power consumption and Wi-Fi communication capability, making it cost-effective in terms of both installation and operation. A visual of the developed board is shown in Fig. 1.

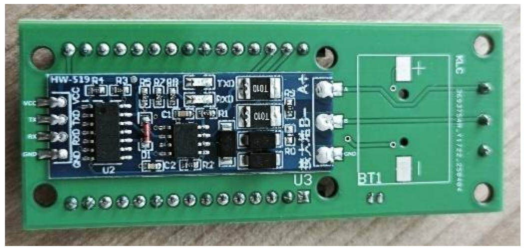

Figure 1. IoT-Based Energy Data Acquisition Board

The central server within the university stores the incoming data with timestamps in an SQL-based database. Additionally, the server hosts a custom-developed web-based interface for data visualization, shown in Fig. 2. Through this interface, users can view voltage, current, power, and energy consumption index. Also, users may call and visualize the data between two dates in this platform.

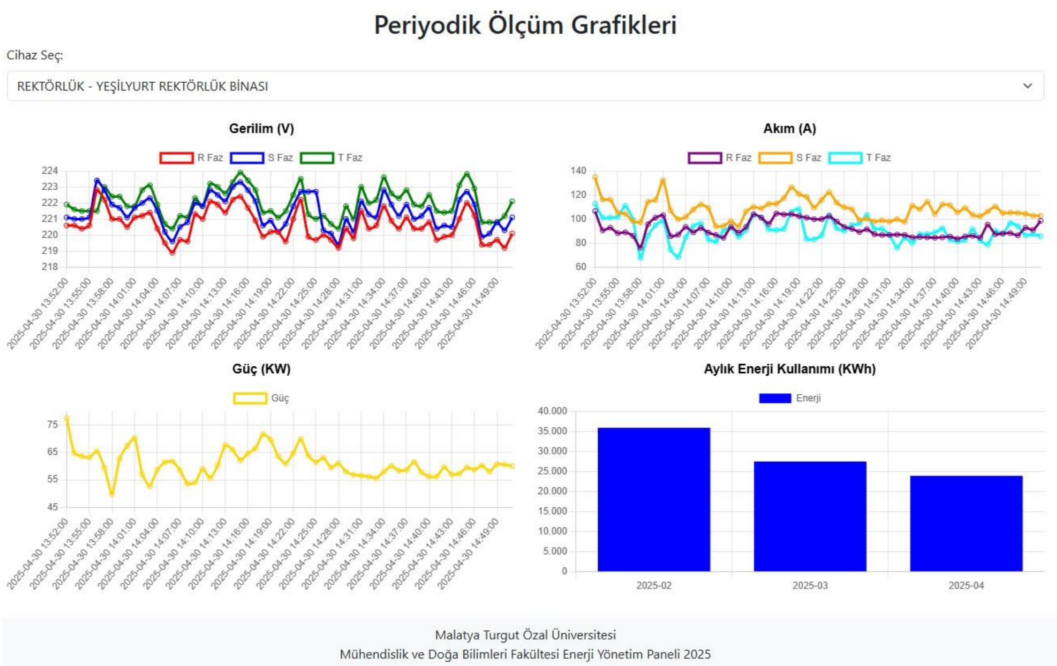

Figure 2. Energy Monitoring System web Interface

2.2. Data Preparation and Load Profile Clustering

The raw data collected from the energy analyzer includes three-phase voltage, three-phase current, active power, reactive power, energy consumption index, and timestamp. This data is stored in a database hosted on the university's central server. Through the designed user interface, users can export the data in .csv format for any desired date range.

Table 1. Clustering Steps of Daily Electricity Consumption Data with K-Means Algorithm (Pseudo Code)

Step	Phase	Key actions (pseudo-code)	Output / purpose
0	**Inputs/ settings**	*Input file* hourlyData.xlsx → columns **Datetime, Power (kW)** *Parameter* kRange = 2…10 – candidate cluster counts	—
1	**Load hourly data**	table ← ReadExcel(hourlyData) timeSeries ← SortByTime(table)	Hour-ordered timetable
2	**Build daily profile matrix**	days← Unique (StartOfDay (timeSeries.Datetime)) profileMatrix ← zeros (numDays, 24) validDays ← [] FOR d IN days hourSlice ← rows (d ≤ t <d+1 day) IF count(hourSlice) == 24 profileMatrix (nextRow, :) ← hourSlice.Power' validDays.Append(d) END END	24-column matrix: **1 day = 1 row**
3	**Standardise (column z-score)**	colMean ← mean (profileMatrix, columns) colStd ← std (profileMatrix, columns) Z ← (profileMatrix − colMean) / colStd	Removes hour-wise scale bias

4	**Select k (Elbow + Silhouette)**	inertiaList ← [] silList ← []
		FOR k IN kRange
		[labels, ~, sumd] ← kmeans(Z,k,replicates)
		inertiaList.Append (Σ sumd) // WCSS
		silList.Append(mean(silhouette(Z,labels)))
		END
		bestK ← kRange[argmax(silList)]
			Choose the k with highest mean silhouette

5	**Run final k-means**	[labelsFinal, centroidsZ] ← kmeans (Z, bestK, replicates) centroidsRaw ← centroidsZ * colStd + colMean	Cluster ID for each day. Centroid profiles in kW
6	**Save results**	outputTable ← {Date = validDays, Cluster = labelsFinal} WriteExcel (outputTable, 'daily_profiles_clusters.xlsx')	Excel file with day–cluster map
7	**Generate plots**	Elbow curve: inertiaList vs kRange Silhouette curve: silList vs kRange For each cluster: 24-h centroid profile	Visual diagnostics & cluster shapes

For this study, data between February 3, 2025—the start of the Spring Semester of the 2024–2025 Academic Year—and April 20, 2025, has been considered. The compiled dataset has been examined in terms of data quality. In the first the step, various data preprocessing techniques were employed to detect outliers, and the outliers have been removed from the dataset. Subsequently, missing data have detected, and new values have been imputed by using available data based on the corresponding date and time of the missing records. After preprocessing, a dataset with dimensions of 1848x9 has been obtained.

The timestamp and power columns have been selected from the dataset, and the resolution of the data converted. The resulting 77 days of hourly consumption profiles have been then subjected to the k-means clustering algorithm in order to group them according to their similarity characteristics. Data preparation process flow diagram is given in Fig.3 and the pseudo code is presented in Table 1.

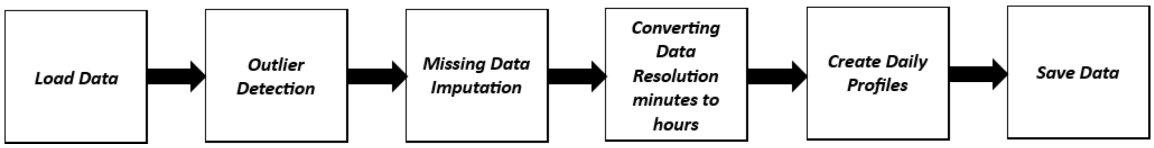

Figure 3. Data Preparation Process Flow Diagram

3. Results and Discussion

The energy consumption data obtained from the energy monitoring system installed in the electricity main distribution panel of Malatya Turgut Özal University CENS building have been segmented by using the k-means clustering algorithm. After data preprocessing, Z-score normalization has been applied to the daily energy consumption data in order to be able to differentiate them in terms of behavior rather than consumption amounts. The optimal number of clusters has determined by evaluating the Elbow method and Silhouette score. In the Elbow method, the k-means algorithm has run for different cluster numbers (k) and inertia (total distance between clusters) values have been calculated for each cluster number. The relationship between the number of clusters (k) and the inertia values are given Fig. 4a. Here, it can be observed how the inertia decreases as k increases. However, after a point (k=3), the rate of decrease in inertia slows down. This point is the elbow point. The evaluation of the silhouette score has been visualized in Fig. 4b. The highest silhouette score has been obtained for three clusters. In both Elbow and Silhoulette score methods, it has been concluded that the optimal number of clusters would be three.

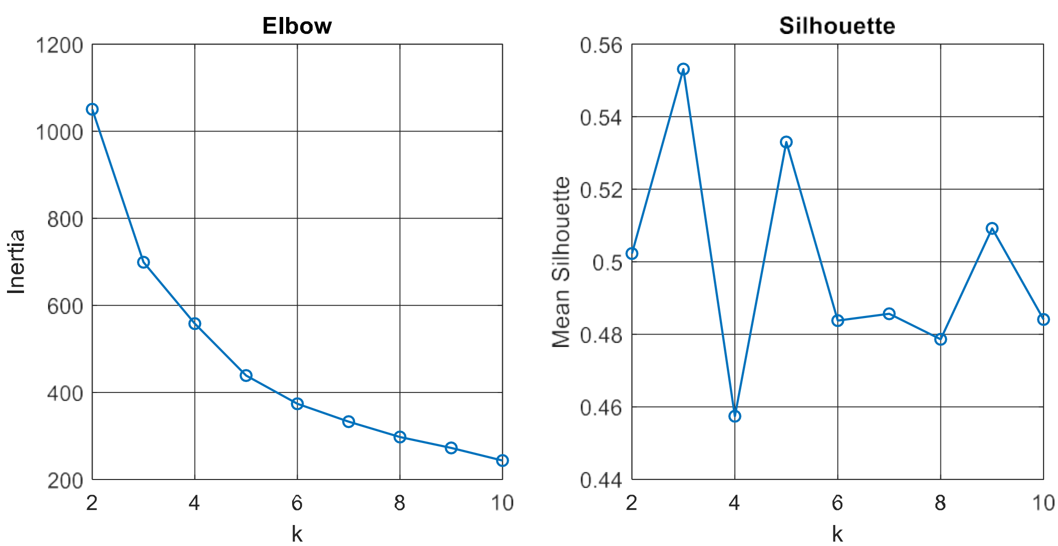

Figure 4. K-means algorithm elbow and silhoulette values

Based on the clustering results obtained using the k-means algorithm, the daily power consumption profiles of the CENS building have been grouped into three distinct clusters. The representative load profile of each cluster, along with the other consumption profiles belonging to the same cluster, have been presented in Fig. 5, 6, and 7. A calendar corresponding to the selected date range has been created and shown in Table 2, where the consumption profile of each day is indicated with the color code of its respective cluster. It has been observed from the results that the highest energy consumption occurred in the C1 cluster, as shown in Fig. 5. The cluster C3 has moderate energy consumption, given in Fig. 7. The C2 profile shown in Fig. 6 exhibits the lowest level of energy consumption. In the figures, the curves plotted with circular markers represent the representative load profile of each cluster, while the pale-colored curves illustrate the daily consumption profiles belonging to that cluster.

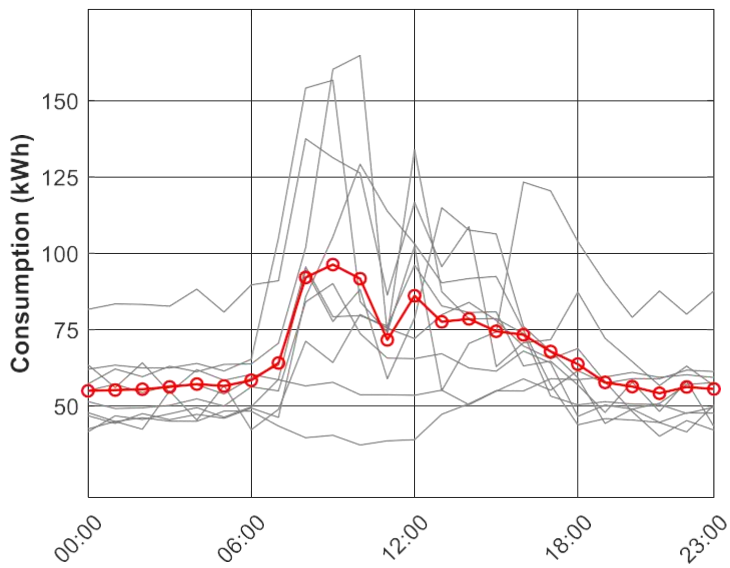

Figure 5. The first cluster and the consumption profiles in the cluster (C1)

In the profiles belonging to Cluster C1, a noticeable increase in energy consumption begins after 06:00 in the morning, reaching its peak between 08:00 and 12:00. This is followed by a short decline during the midday hours, after which a gradual decrease is observed throughout the afternoon. For the remainder of the day, energy consumption continues to decline toward the evening and remains at a steady level throughout the night.

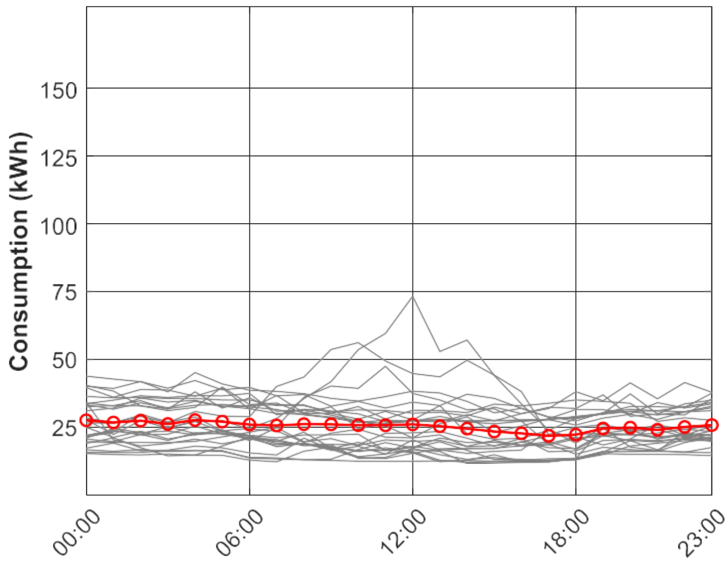

Figure 6. The second cluster and the consumption profiles in the cluster (C2)

In cluster C2, energy consumption is constant and low throughout the day. This consumption curve can be associated with weekends and holidays when the use of the building is at a low level.

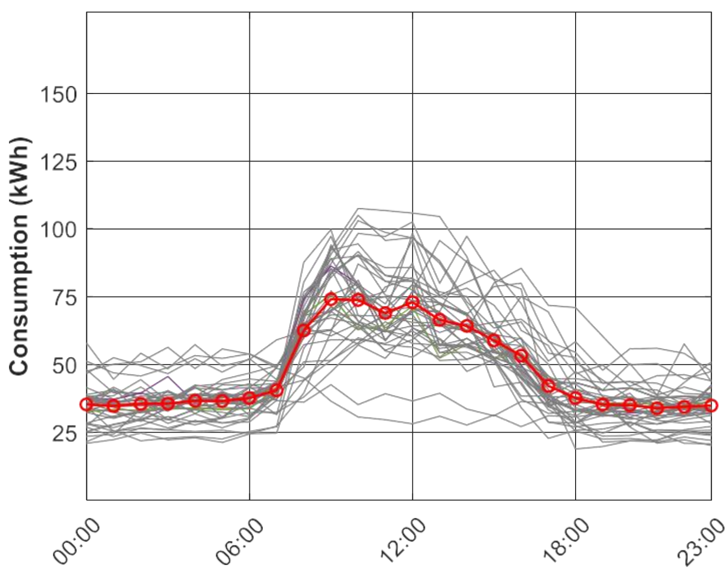

Figure 7. Third cluster and consumption profiles in the cluster (C3)

The average consumption curve given in Fig. 7 reveals that energy use in the building increases from the morning hours and reaches its peak value during working hours. High-energy consumption is observed between 09:00 and 16:00, which clearly reflected the time periods when the building was in active use.

The distribution of the three different energy consumption patterns (C1, C2, and C3) across months, weeks, and days is presented in Table 2. Upon examining the table, it is observed that Cluster C1 is valid for 10 days during the month of February. In addition to the natural gas-based central heating system in the classrooms and offices of the CENS building, there are also VRF (Variable Refrigerant Flow) air conditioning systems powered by electricity. Analyzing the temperature data for the selected date range reveals that the consumption profiles in Cluster C1 correspond to the coldest days. The high levels of energy consumption are associated with the usage of the VRF systems. The weather data for February is provided in Table 3. It has been observed that the C2 cluster corresponds to the dates of weekends and public holidays (Ramadan Feast: 31.03.2025 – 04.04.2025). Cluster C3, on the other hand, is consistently observed on weekdays, representing days when the building's routine academic and administrative activities are in operation. This analysis reveals the temporal distribution of energy consumption patterns and serves as a valuable tool in the development of energy efficiency strategies.

Table 2. Distribution of K-means Cluster Results on the Weekly Calendar

C1 / *C2* / *C3*	MONDAY	TUESDAY	WEDNESDAY	THURSDAY	FRIDAY	SATURDAY	SUNDAY	
week 1	**3**	**4**	**5**	**6**	**7**	8	9	**FEBRUARY**
week 2	**10**	**11**	**12**	**13**	**14**	15	16	
week 3	**17**	**18**	**19**	**20**	**21**	22	23	
week 4	**24**	**25**	**26**	**27**	**28**	1	2	**MARCH**
week 5	**3**	**4**	**5**	**6**	**7**	8	9	
week 6	**10**	**11**	**12**	**13**	**14**	15	16	
week 7	**17**	**18**	**19**	**20**	**21**	22	23	
week 8	**24**	**25**	**26**	**27**	**28**	29	30	
week 9	31	1	2	3	4	5	6	**APRIL**
week 10	**7**	**8**	**9**	**10**	**11**	12	13	
week 11	**14**	**15**	**16**	**17**	**18**	19	20	

Table 3. Minimum Temperature Measured in February (*°C*)

C1 / *C2* / *C3*	MONDAY	TUESDAY	WEDNESDAY	THURSDAY	FRIDAY	SATURDAY	SUNDAY	
week 1	**0,0**	**-0,6**	**0,3**	**-4,3**	**-5**	-4,7	-5,4	**FEBRUARY**
week 2	**-1,5**	**-2,6**	**-2,1**	**-2,9**	**-7,6**	-9,6	-4,3	
week 3	**-3,8**	**-1,6**	**-0,4**	**-8,1**	**-9,5**	-10	-11	
week 4	**-14**	**-12**	**-9,6**	**-6,0**	**-3,5**			

Conclusions

In this study, three-phase voltage, three-phase current, active and reactive power, and total energy consumption data collected at a one-minute resolution using a developed IoT-based energy monitoring device connected to an energy analyzer installed in the CENS building at Malatya Turgut Özal University campus. The data collected have been stored on a central server, outliers detected and removed, missing values have been imputed using appropriate methods, and hourly averages have been calculated to prepare a suitable dataset for analysis. Based on daily consumption profiles between February 3 and April 20, 2025, clustering analysis revealed three distinct energy consumption behaviors within the campus building. These clusters have meaningfully differentiated based on weather conditions, building occupancy intensity, and the presence of students and staff.

The clustering results showed that energy consumption patterns are not only temporally dependent but also strongly correlated with weather conditions, user density, and weekdays. Through visualizations, the cluster membership of each day has been presented in a matrix format, providing an intuitive overview of the building's energy usage rhythm. Such analyses offer valuable insights for the development of campus-scale energy management strategies, creating awareness, and identifying potential areas for energy savings. In conclusion, the study demonstrated that a low-cost IoT-based monitoring system can be effectively used in large-scale complex structures such as university campuses, both for real-time monitoring and as a long-term decision support tool.

Acknowledgements

The authors would like to express their sincere gratitude to Malatya Turgut Özal University for providing the infrastructure and technical support necessary for the implementation of the energy monitoring system. Institutional encouragement and access to field data were invaluable in the successful execution of this study.

References

[1] International Energy Agency. Energy Efficiency 2021. IEA Publications; 2021.
[2] United Nations. Sustainable Development Goals Report. UN Publications; 2022.
[3] Mir U, Abbasi U, Mir T, Kanwal S & Alamri S. Energy management in smart buildings and homes: current approaches, a hypothetical solution, and open issues and challenges. IEEE Access 2021;*9*:94132-94148.
[4] Bandyopadhyay D & Sen J. Internet of things: Applications and challenges in technology and standardization. Wireless personal communications 2011;*58*:49-69.
[5] Gubbi J, Buyya R, Marusic S & Palaniswami M. Internet of Things (IoT): A vision, architectural elements, and future directions. Future generation computer systems 2013;29:1645-1660.
[6] Zhu N, Anagnostopoulos A & Chatzigiannakis I. On mining iot data for evaluating the operation of public educational buildings. IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops); 2018, p. 278-283.
[7] Mylonas G, Amaxilatis D, Tsampas S, Pocero L, & Gunneriusson J. A methodology for saving energy in educational buildings using an IoT infrastructure. 10th international conference on information, intelligence, systems and applications (IISA); 2019, p. 1-7.
[8] Chicco G. Overview and Performance Assessment of the Clustering Methods for Electrical Load Pattern Grouping. Energy 2012;42:68-80.
[9] Czétány L, Vámos V, Horváth M, Szalay Z, Mota-Babiloni A, Deme-Bélafi Z & Csoknyai T. (2021). Development of electricity consumption profiles of residential buildings based on smart meter data clustering. Energy and Buildings 2021;252:111376.