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Building Power Demand and Energy Consumption Forecasting Using a Data-Driven Model: a Case Study in a Student Hostel

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ABSTRACT

Accurate forecasting of building power demand and energy consumption is essential for optimizing energy usage, improving efficiency, reducing costs, and ensuring sustainability. However, this prediction process is challenging due to factors such as variable occupancy, unpredictable occupant behavior, seasonal weather changes, data limitations, complex system interactions, and other external influences. This study develops a data-driven model based on historical electrical power data to predict the power demand and energy consumption of a student hostel. The historical data, recorded at five-minute intervals, was collected by logging the main incoming power supply using a power quality analyzer at the main switch block. Based on the power profile, the model was developed for four distinct time frames: falling, baseload, rising, and peak-load periods. Two key independent variables - minutes past midnight and type of day (weekday or weekend)—were considered as primary influences on power demand. Unlike previous models, this study employed MATLAB programming to optimize correlation modeling using the statistical approach of the power-law function. Results indicate that eighth- to ninth-degree polynomial fits provide the best power forecasting, achieving R^2 values as high as 0.9989. However, the prediction of power demand and energy consumption during peak-load periods on weekends was more complex, with a power correlation R^2 value of just 0.6100. Model accuracy assessments across different time frames and days showed that the developed model could predict power demand and energy consumption with a deviation of less than 5% compared to actual measurements. These findings demonstrate that a predictive model using only two independent variables, a power-law function, and polynomial fits up to the eighth and ninth degrees can effectively forecast power demand and energy consumption of the hostel. This model is expected to be valuable for future demand response (DR) programs, supporting the analysis of DR initiatives and the optimization of energy efficiency strategies. Future research could explore the integration of additional significant parameters alongside machine learning techniques to further enhance model accuracy. Factors such as outdoor air temperature, examination days, and a more detailed occupancy rate could be investigated and incorporated into future model development. This would allow for a more comprehensive evaluation of various energy consumption scenarios and their potential impact.

1. INTRODUCTION

Records indicate that the energy sector accounts for nearly 75% of global greenhouse gas (GHG) emissions [1]. One of the primary reasons for this is the significant reliance on non-renewable sources for electricity generation. In terms of electricity consumption, buildings rank as the third-largest energy consumers worldwide and are responsible for approximately a quarter of global CO_2 emissions [2]. In the context of Malaysia, data from the Energy Commission shows that in 2020, 81.7% of electricity generation depended on two non-renewable sources: coal and gas [3]. Meanwhile, buildings in Malaysia account for 14.3% of total energy consumption, with 53% of electrical energy used by the residential and commercial sectors [4]. Since electricity generation from non-renewable sources produces harmful greenhouse gas emissions, inefficient energy consumption in buildings significantly increases electricity demand from power plants, thereby contributing to higher GHG emissions.

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According to records, the Grid Emission Factor of Peninsular Malaysia in 2021 indicates that the consumption of 1 kWh of electricity contributed 758 g of CO_2 emissions to the environment [5]. Efficient energy use in buildings can help reduce dependency on non-renewable sources, thereby extending the lifespan of these resources. Indirectly, this ensures the continuous availability of electricity at an affordable cost while fostering a culture of energy conservation and efficiency. Additionally, it supports environmental protection by mitigating the severe impacts of climate change, ultimately promoting long-term sustainability.

In this regard, energy-efficient buildings, supported by an effective operational strategy, play a vital role in achieving this sustainability target [4]. However, to develop an effective operational strategy, the energy consumption characteristics of the building must first be clearly understood. Therefore, how building energy consumption characteristics can be effectively analyzed and modeled for different types of buildings is becoming increasingly significant and is the main research focus of this study. This understanding can lay the foundation for future research aimed at developing an optimal building operation strategy.

Previous studies have identified several factors that determine energy consumption characteristics and how energy is used. Occupant behavior is one of the key factors influencing energy usage in buildings [6]. Different types of buildings (*e.g.*, office buildings, commercial buildings, residential apartment buildings, *etc.*) have distinct energy consumption characteristics. For example, commercial building energy consumption patterns generally follow daily activities and weather conditions [7]. Meanwhile, in residential buildings, energy consumption patterns largely depend on occupant behavior and the number of hours spent inside the building. As a result, Sepehr *et al.* [8] and Wei and Bai [9] emphasized that studying energy consumption should consider different time scales or short-term periods for accurate predictions. In summary, understanding energy consumption characteristics is essential for improving decision-making aimed at reducing energy use and CO_2 emissions. This knowledge helps assess various building operation strategies and enhances demand and supply management. To date, limited studies have explored energy consumption characteristics in residential and non-residential buildings [7]-[15].

Choi *et al.* [10] conducted a series of case studies and resident surveys to analyze energy consumption in high-rise apartment buildings based on building use and shape. Under the building use classification, they found that residents of mixed-use apartments demonstrated greater engagement in active heating management and frequently adjusted their indoor activities. However, they consumed more electricity, especially during the summer, compared to those living in standard residential apartments, leading to higher CO_2 emissions in mixed-use apartments. Under the building shape classification, they found that for common areas, tower-type buildings consumed 48% more energy but only 90% of the gas consumption compared to plate-type buildings.

Khoshbakht *et al.* [12] characterized energy use and applied stochastic frontier analysis as a benchmarking technique for higher education buildings. In terms of activity type, they found that buildings primarily used for research and academic offices had the highest and lowest energy intensity benchmarks at 216 and 137 kWh/m²/year, respectively. In terms of discipline, Science and Health buildings had the highest and lowest energy intensity benchmarks at 164 and 136 kWh/m²/year, respectively.

Meanwhile, energy use forecasting is crucial for effective building energy planning, management, and optimization [16]-[18]. In the field of data-driven energy consumption prediction modeling, a previous study [15] reviewed that 19% of these models focused on residential buildings, while 57%, 12%, 15%, 4%, and 12% were developed for predicting hourly, sub-hourly, daily, monthly, and yearly energy consumption, respectively.

Sepehr *et al.* [8] considered residential house type and individual appliance load profiles in their daily load profile modeling. Zhu *et al.* [7] developed a prediction model to quantify daily building load profiles using historical energy consumption data from metering systems, along with environmental and holiday information. They claimed that their prediction model could detect anomalies in energy consumption by comparing predicted statistics with observed data.

Castillo *et al.* [19] utilized the Monte Carlo technique to create actual daily averaged demand profiles. They performed 100 simulations to model the daily demand profile of each appliance group in the building. Since each profile was generated based on probabilistic and random variables, the approach allowed for multiple possible scenarios for each day, making the model more reflective of real user behavior. Finally, daily and monthly energy consumption were calculated based on each daily demand profile. Recently, Ghenai *et al.* [20] forecasted short-term building electrical load using an adaptive neuro-fuzzy inference system. The developed model was considered highly accurate in predicting building electrical load, with R-values ranging from 0.968 to 0.980 for all forecasting time horizons. More recently, Tsala *et al.* [21] used weather forecast meteorological models for building energy simulations. This study focused on the impact of insulation materials on energy efficiency and environmental sustainability in a multifamily building, extending its findings to anticipate future challenges in 2050 and offering practical insights for building performance and climate adaptation.

In general, understanding building energy consumption profiles, especially for buildings classified as significant energy users, is crucial for accurate energy consumption prediction. Additionally, understanding energy profiles is essential for identifying energy-saving measures and setting actionable targets that can be planned and implemented to improve building energy efficiency. Indirectly, this promotes a culture of energy conservation and efficiency while contributing to environmental sustainability. Aligning with global and national goals, such as achieving net-zero carbon emissions by 2050, is a key priority in this context. Table 1 summarizes previous studies related to building energy forecasting.

Table 1. Summary of previous studies related to building energy forecasting.

Author	Type of Building	Objective of Study	Technique of Modeling	Advantages	Disadvantages
Sepehr *et al.* [8]	Occupancy-based housing	To model and analyze residential electricity consumption using a bottom-up approach to better understand consumer behavior and improve energy management	Bottom-Up Modeling Method	• Captures consumer behavior by models individual appliance usage and consumer behavioral patterns, providing a more detailed consumption profile. • Integrates data between energy bills and household surveys lead to good accuracy of the model.	• Requires details comprehensive and data on appliance usage, consumer behavior, and environmental conditions, which may not always be available. • Simulating a large number of households at high resolution demand significant computational resources
Khoshbakht *et al.* [12]	Academic buildings except student hostel	To understand energy use characteristics of different types of buildings in higher education campuses and to establish an energy benchmark system	Stochastic Frontier Analysis (SFA)	• More accurate efficiency estimation by separating random errors from actual inefficiencies • Suitable for analyzing many buildings for benchmarking analysis.	• If there are no measurement errors, some inefficiencies may be wrongly classified as statistical errors. • SFA does not determine efficiency based on the performance of just one building.
Zhu et al [7]	Commercial buildings	To develop a data-driven energy management framework using smart metering data to analyze building load profiles, detect anomalies, and improve energy efficiency in commercial buildings	Data-Driven Modeling with Machine Learning	• Leverages real-time energy consumption data for accurate analysis. • Detects Anomalies – Identifies abnormal energy consumption patterns for better facility management. • Uses machine learning to forecast future building energy usage.	• Machine learning models require significant processing power. • Model performance depends on selecting the right algorithms and parameters, thus requires expert tuning
Castillo *et al.* [19]	Academic buildings except student hostel	To model and analyze energy consumption in a university campus building	Monte Carlo Method	• Incorporates random variations in energy usage, providing a more realistic model. • High flexibility method where it can be applied to various types of buildings and adapted to different energy systems	• Requires a large amount of input data, including historical energy consumption and probability distribution. • Running multiple simulations requires significant processing power.
Ghenai *et al.* [20]	Academic buildings except student hostel	To develop a short-term energy consumption forecasting model for a university	Adaptive Neuro-Fuzzy Inference System (ANFIS)	• Combines artificial neural networks and fuzzy logic for accurate energy forecasting. • Effective for Short-Term	• Training can be time-consuming, especially with large datasets • Complex model

		building to improve energy planning and management		Forecasting – Performs well in short term energy consumption prediction within minutes to hours	needs expert tuning of parameters, including membership functions and training algorithms
Tsala *et al.* [21]	Multi-unit residential complex	To analyze the impact of insulation materials on energy efficiency and environmental sustainability in a multi-unit residential complex, considering future climate conditions	Building Energy Simulation (BES) with Weather Forecast Meteorological Models	• Allows detailed modeling of heating and cooling needs based on real climate data • Assesses different insulation materials and their impact on future climate conditions. • Helps in selecting the best materials for sustainability and energy efficiency	• Requires detailed information on building materials, HVAC systems, and local climate data. • Simulations can be complex and time consuming, needing specialized software and expertise. • Results depend on input assumptions, which may not fully capture real world variation.

As listed in Table 1, numerous studies on energy consumption characteristics and model forecasting, especially for residential buildings, have been conducted over the past few years. The proposed models are generally complex, requiring large and varied input data, thus necessitating intricate computer simulation programming. This complexity is mainly due to the intricate energy use characteristics of the buildings under study.

Apart from that, research specifically focusing on student hostels remains limited. Given that student hostels can be significant energy consumers in Institutions of Higher Learning (IHL)—depending on their size and academic calendar—this study is considered essential. Additionally, occupant behavior in student hostels, characterized by lower appliance complexity compared to typical residential buildings, may require a different modeling approach—one that is less complex yet maintains high accuracy. In addition, to the authors' knowledge, modeling using the statistical approach of the power-law function has never been conducted. Therefore, it is necessary to explore how the power-law function (polynomial fits) can be utilized to model energy consumption with less complex characteristics while achieving the highest possible accuracy.

Therefore, this paper aims to analyze, understand and model the power demand profile of a student hostel. Furthermore, it seeks to determine whether it is appropriate to model the power profile characteristics using the statistical approach of the power-law function (polynomial fits), with only two independent input variables that significantly influence power demand: minutes past midnight and the type of day (weekday or weekend) for power and energy forecasting. In this study, a specific student hostel in an IHL will be selected as a case study. Due to variations in occupancy rates throughout the year, the maximum possible occupancy rate during an instructional or lecturing session will be chosen.

Firstly, the power demand of the building will be measured and analyzed. The collected data will then be used to develop a prediction model. This model is expected to accurately estimate the building's power demand and energy consumption at different times of the year. Details of the methodology are presented in Section 2. In the future, the model is anticipated to serve as a baseline for identifying potential energy-saving measures and setting energy-saving targets, contributing to improved energy efficiency in the building. Additionally, the model framework can be applied to various types of buildings with similar complexity.

2. METHODOLOGY

2.1 Building Information and Description

The campus area of an IHL consists of office buildings, educational buildings (faculties), a health center, a sports complex, student hostels, religious buildings, food courts (cafeterias), a library, and a safety office building, making it comparable to a small city. As a result, the amount of electricity consumed in this IHL is significant, necessitating energy conservation and efficiency practices to achieve the goal of a sustainable city and society, as highlighted in SDG 11 (Sustainable Cities and Communities) by the United Nations.

In this study, a student hostel within an IHL, consisting of five blocks with nine levels each and an additional cafeteria block, is chosen as a case study. Figure 1 presents a top view alongside a side view of two blocks and the cafeteria buildings. Each block accommodates 1,000 students and includes a hostel management office, which operates from 8:00 am to 5:00 pm. Additionally, each block is provided with one head fellow house and two fellow houses.

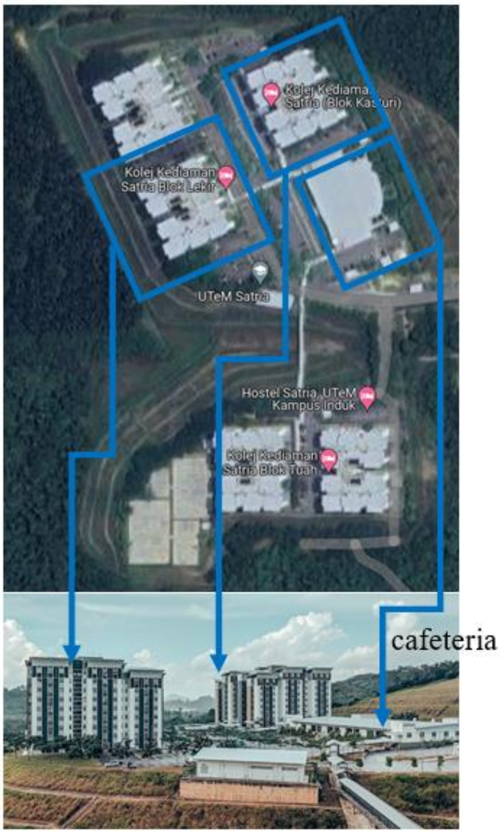


Fig. 1. The student hostel.

In general, the power demand and energy consumption of this hostel can be considered unique, as they depend on the current academic session. The academic session whether it is the lecture/instructional period, mid semester break, study week, end-semester break, or a long public holiday affects the occupancy rate and the level of student activity related to energy usage. Consequently, the intensity of hostel energy usage is also highly influenced by the academic session during any given semester.

Accurately predicting energy consumption in the hostel is essential, as the hostel is a major energy consumer within the IHL, particularly during the lecture/instructional period. Achieving high prediction accuracy for this significant energy consumer will allow for effective corrective actions to be planned and implemented, leading to substantial energy performance improvements across the entire IHL. Data from the IoT Energy Response System of the IHL indicates that the hostel accounts for the highest electricity consumption in the IHL, approximately 18.85% during the lecture/instructional period, as shown in Figure 2. For this reason, the hostel has been selected as the case study.

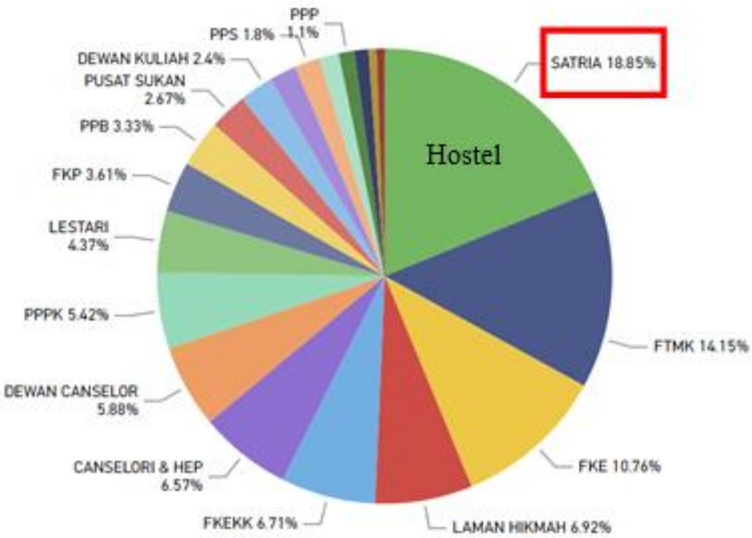


Fig. 2. Load opportuning in January 2024 [22].

2.2 Study Approach

Figure 3 shows the methodology flowchart of this study. The main purpose of the site investigation is to assess the suitability of the hostel and determine the appropriate location for data logging. The total power demand was recorded at the main incoming power supply, located at the main switch block (MSB), using two calibrated Chauvin Arnoux power quality analyzers (Figure 4), model C.A 8435. During this field data measurement, flexible current sensors were clamped onto the incoming bus bars in the MSB. Data was recorded for two weeks at five-minute intervals. The data is considered complete if it is logged continuously for two consecutive weeks at five-minute intervals, without any missing entries or abnormalities.

Therefore, total power in a day, $P_{1\ day}$ can be calculated as in Equation 1, where n represents the total number of data points in the dataset per day.

$$P_{1\,\text{day}} = \sum P_n \tag{1}$$

With a five-minute time interval per day, the total number of data points recorded from 12:00 am to 11:55 pm is 288. The daily energy consumption, $E_{1\,\text{day}}$ can be calculated as follows:

$$E_{1\,\text{day}} = \frac{P_{1\,\text{day}}}{12} \tag{2}$$

If m is the total number of data points in the dataset between 8:00 am and 10:00 pm, the Maximum Demand (MD) for the day is predicted and defined as the highest power measured within this time period, where:

$$MD = \text{MAX}(P_1, P_2, ..., P_m) \tag{3}$$

The power consumption prediction model is formulated and proposed based on the real power profile characteristic. In general, the average power consumption at t minutes past midnight, $\bar{P}_{data,t}$ based on a total of q sampled power consumption data points at the respective t, $P_{data,t}$ is determined by using Equation 4 where:

$$\bar{P}_{data,t} = \frac{\sum^{q} P_{data,t}}{q} \tag{4}$$

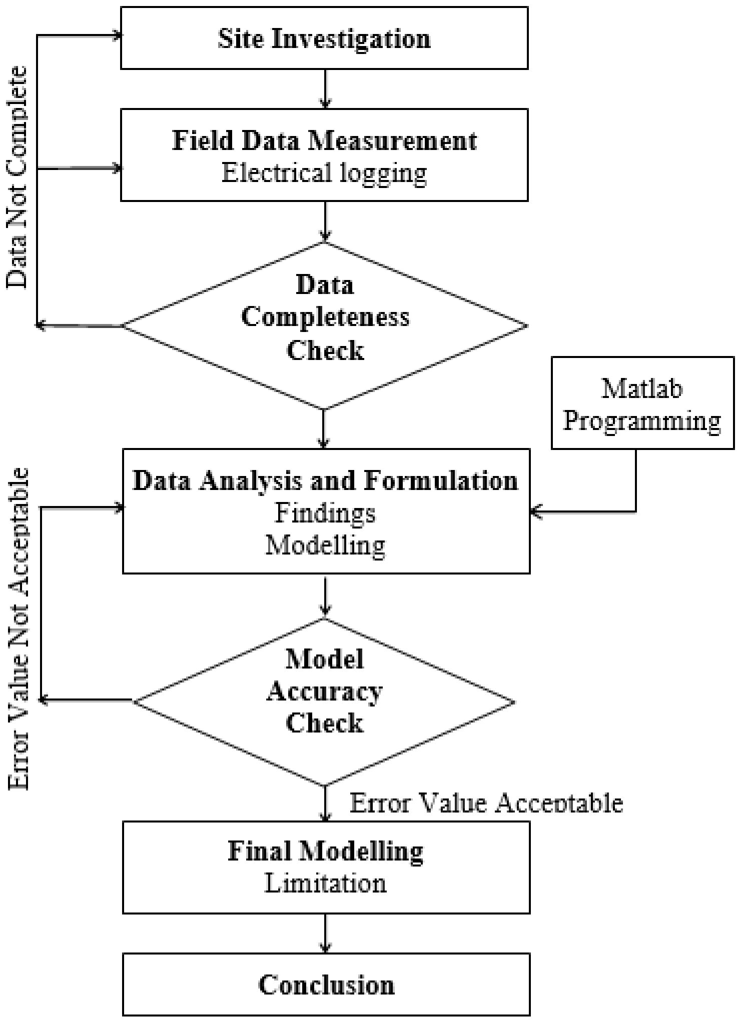


Fig. 3. Methodology flowchart.

Fig. 4. Power logging process using power quality analyzers.

The predicted power consumption model correlation at t minutes past midnight, $P_{predict,t}$ is developed based on the dataset $\bar{P}_{data,t}$. Power demand in a student hostel is expected to vary with minutes past midnight (t) due to daily routines. The type of day is also expected to influence demand, with weekdays having lower daytime consumption as students attend classes, while weekends show higher all-day usage due to more flexible schedules. Therefore, t and the type of day (either a weekday or a weekend) are expected to be key factors in accurately predicting power demand. Since $P_{predict,t}$ is primarily a function of minutes past midnight (t) and the type of day (either a weekday or a weekend), this relationship can be mathematically expressed in Equation 5. The general form of Equation 5 for weekday and weekend datasets is then fitted using a power-law function, as shown in Equation 6, where a is a constant and r is the maximum power integer. MATLAB programming is used to determine the best correlation.

$$P_{predict,t} = f\left(t, type\ of\ the\ day\right) \quad (5)$$

$$P_{predict,t} = a_r t^r + a_{r-1} t^{r-1} + \ldots + a_2 t^2 + a_1 t + a_0 \quad (6)$$

The predicted energy consumption within a specified time frame, from t_1 to t_2, and for a given type of day (weekday or weekend), denoted as $E_{predict,t_1\text{-}t_2}$, can be computed by integrating the corresponding $P_{predict,t}$ correlation (Equation 6) over the specified time interval, as expressed in Equation 7.

$$E_{predict,t_1\text{-}t_2} = \int_{t=t_1}^{t=t_2} P_{predict,t}\, dt \quad (7)$$

The model accuracy check is evaluated using percentage of error (% error), as defined in Equation 8, where $P_{actual,t}$ is the actual power consumption at t minutes past midnight.

$$\%\ \text{error} = \frac{P_{predict,t} - P_{actual,t}}{P_{actual,t}} \times 100\% \quad (8)$$

Similarly, the % error for energy consumption prediction can be evaluated using Equation 9, where:

$$\%\ \text{error} = \frac{E_{predict,t_1\text{-}t_2} - E_{actual,t_1\text{-}t_2}}{E_{actual,t_1\text{-}t_2}} \times 100\% \quad (9)$$

In addition, mean absolute percentage error ($MAPE$) is also used to measure the accuracy of a forecasting or predictive model. Generally, $MAPE$ can be computed as in Equation 10 where s, y_i and $\bar{y}_i$ are the total number of prediction data points, actual value and predicted value, respectively [23].

$$MAPE = \frac{1}{s}\sum_{i=1}^{s}\left|\frac{y_i - \bar{y}_i}{y_i}\right| \times 100\% \quad (10)$$

Moreno *et al.* [24] highlighted that a MAPE of less than 10% is considered highly accurate for forecasting. In this power and energy forecasting study, the predictive model is deemed acceptable if the individual percentage error and MAPE are less than 5% [25]. Otherwise, a new modeling formulation will be developed and refined using the optimal combination of power integer r and the time-scale approach, while also incorporating additional independent variables that influence power demand and energy consumption.

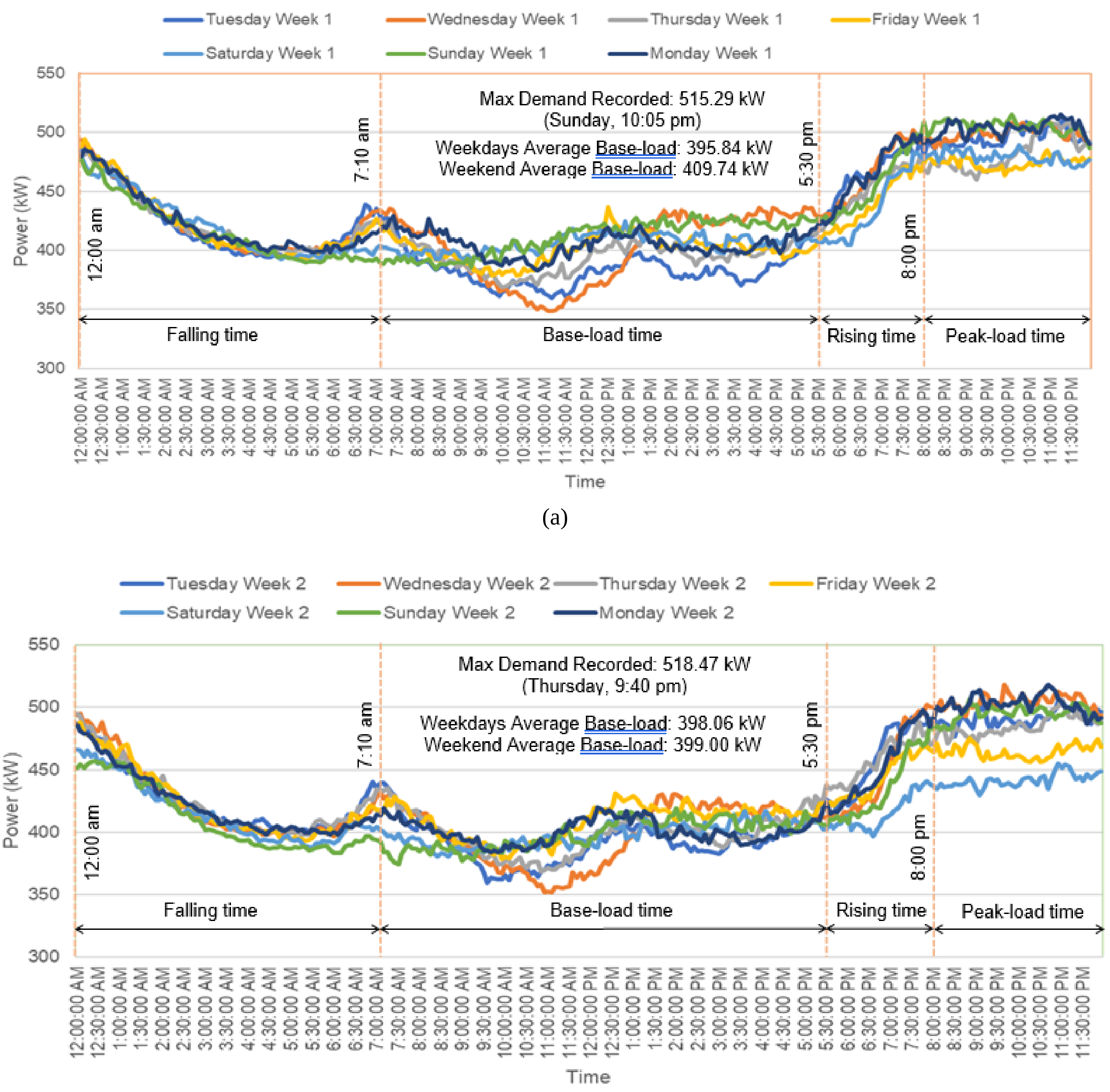
3. RESULTS AND DISCUSSION

3.1 *Electricity Load Profiles*

The electrical profile for two weeks, obtained through electrical logging during the lecture/instructional session in early November 2023, is shown in Figure 5. All measured days exhibit a similar pattern, with the highest power demand (MD) recorded between 8:00 pm and 12:00 am, regardless of the type of day.

As proposed by Sepehr *et al.* [8] and Wei and Bai [9], energy consumption patterns should consider different time scales or short-term periods for accurate prediction. Therefore, it is reasonable to divide the power profile in Figure 5 into four (4) distinct time scales: falling time, base-load time, rising time, and peak-load time. The corresponding time frames are as follows: falling time (12:00 am – 7:10 am), base-load time (7:10 am – 5:30 pm), rising time (5:30 pm – 8:00 pm), and peak-load time (8:00 pm – 12:00 am).

During falling time, power demand steadily declines, suggesting reduced activity as students sleep. During base-load time, power demand stabilizes at lower levels during the daytime, likely due to students attending classes or being outside. Additionally, the weekday base load is slightly lower than on weekends, implying that students spend more time outside for classes on weekdays. The higher base load on weekends also suggests prolonged in-room activities, such as entertainment and electronic device usage. Meanwhile, the nearly equal average base load between weekends and weekdays in Week 2 indicates that weekend activities maintained steady energy consumption.



(a)

(b)

Fig. 5. Electricity load profiles. (a) Week 1, (b) Week 2.

A significant increase in demand begins approximately between 5:30 pm and 8:00 pm (rising time) as students return, start using electrical devices, and prepare for the night. The highest recorded peak load occurs between 8:00 pm and 12:00 am (peak-load time). The maximum demands recorded during this period were 515.29 kW on Sunday at 10:05 pm (weekend) and 518.47 kW on Thursday at 9:40 pm (weekday), respectively. From a weekly perspective, the highest recorded peak varies in both timing and intensity. In Week 1, the peak load on Sunday night may be linked to students preparing for the upcoming week, whereas in Week 2, the peak load on Thursday night suggests increased activity before the weekend, possibly due to assignments, entertainment, or social events. However, this MD does not impact the energy cost for the IHL, as the MD charged by the utility provider occurs during office hours (8:00 am to 5:00 pm).

Based on these profile findings, it is proposed that future energy efficiency strategies should focus on peak-load time (8:00 pm to 12:00 am). Additionally, weekend energy management should be considered due to relatively high base loads. However, load-shifting strategies are not recommended, as the MD and peak energy consumption of the hostel occur outside office hours, typically during the off-peak period, when the energy cost under tariff C1-OPTR (USD 0.064/kWh) is relatively lower, as compared to the on-peak period (USD 0.081/kWh). Note that 1 USD is equivalent to MYR 4.5310.

Based on this energy profile, the building's daily energy consumption is calculated and visualized in Figure 6. In total, the hostel consumed 71,786.36 kWh and 71,298.21 kWh of electricity in Weeks 1 and 2, respectively. Assuming a four-week month, the estimated monthly electricity consumption for the hostel is approximately 286,169.15 kWh. Validation against the energy dashboard of the IHL for this hostel shows that the actual consumption for that month was 294,282 kWh. The difference of approximately 2.76% is considered acceptable.

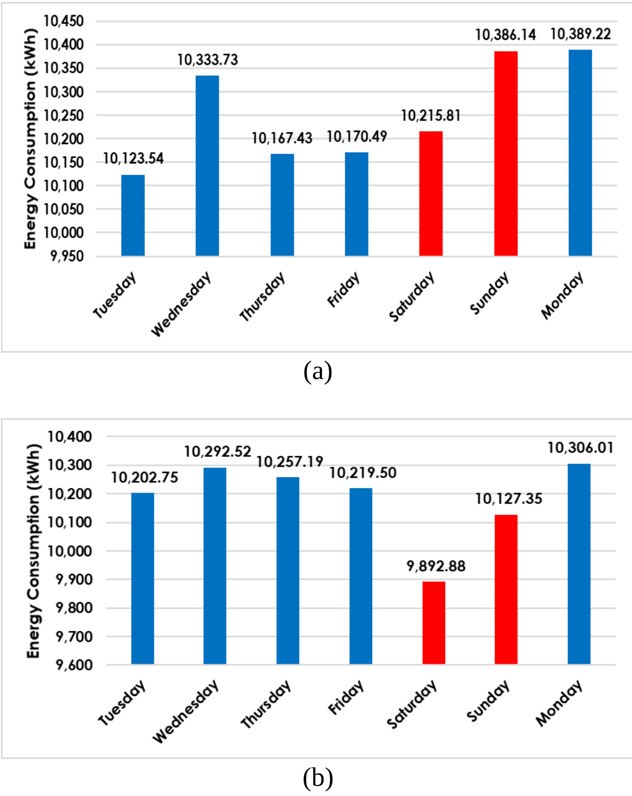


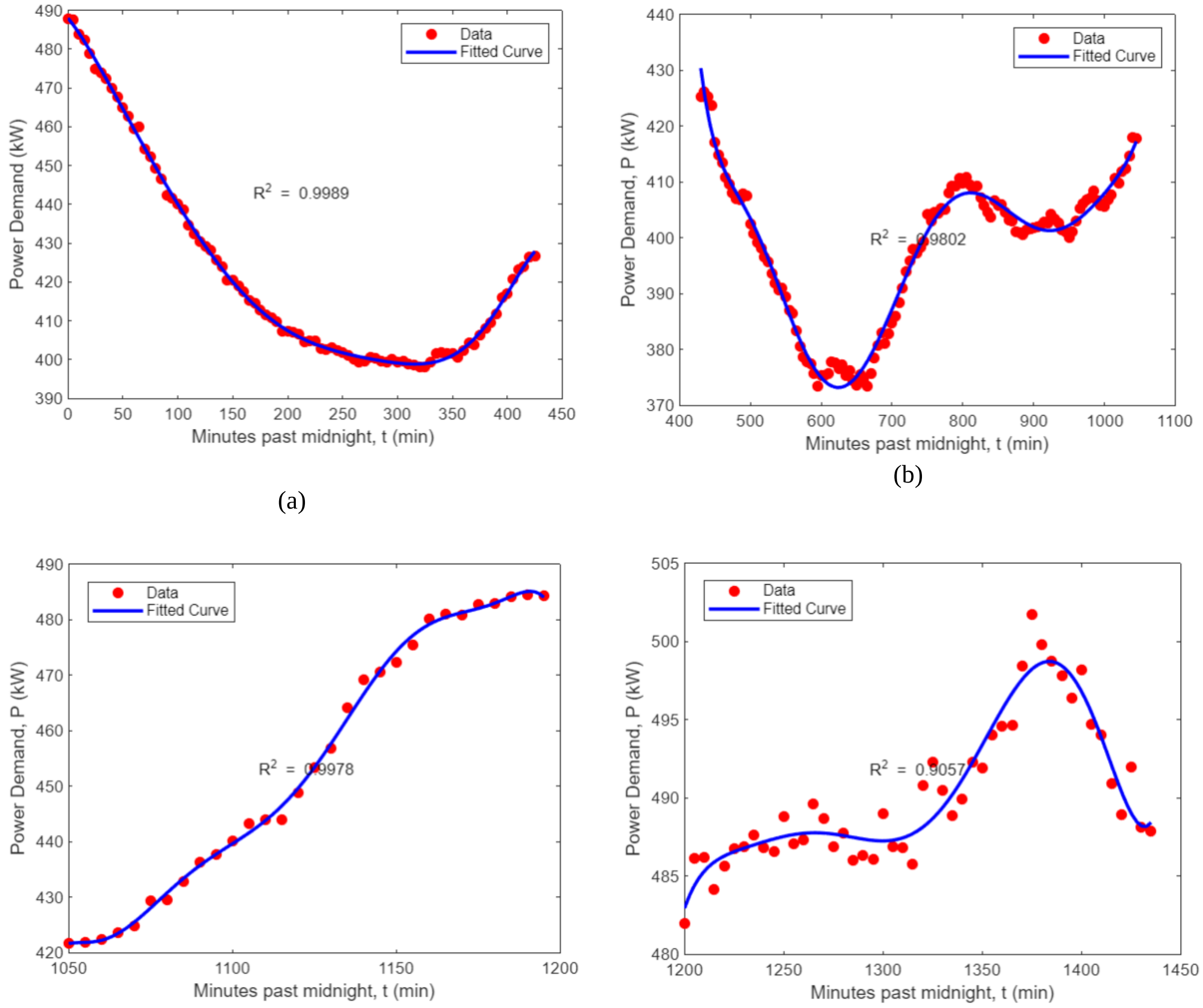
Fig. 6. Electricity load profiles. (a) Week 1, (b) Week 2.

3.2 Power Demand Correlation and Power Consumption Predictions

Based on the power profile in Figure 5 and the recommendations of Sepehr *et al.* [8] and Wei and Bai [9], a power consumption prediction model is proposed at different time scales to enhance accuracy. Four-time scales are introduced, and the power consumption prediction demonstrates excellent R^2 values, as shown in Figure 7 and Table 2 for weekdays, and Figure 8 and Table 3 for weekends. Correlations were fitted and optimized using MATLAB programming through a statistical power-law function (polynomial fit) approach.

In Figure 7, it is observed that the eighth-degree polynomial fit produces good R^2 values, thus providing the best correlation for power prediction across all time scales. Note that t represents the actual time past midnight in minutes. For example, 1:30 am corresponds to t = 90 minutes. As shown in Figure 7 and Table 2, the highest R^2 value (0.9989) is observed for the falling time, followed by the rising time (0.9978), base-load time (0.9802), and peak-load time (0.9057).

The higher R^2 values, particularly during falling time, rising time, and base-load time, indicate consistent and predictable energy usage patterns on weekdays. However, during peak-load time, energy consumption becomes highly dependent on individual behavior, as most occupants are present in the hostel. Variations in energy awareness and time allocation contribute to potential deviations in the energy consumption profile. Nevertheless, the R^2 value of 0.9057 is considered sufficiently reliable for power demand and energy consumption prediction.



(a) (b) (c) (d)

Fig. 7. Power demand correlation prediction base on time scale for weekdays. (a) Falling time, (b) Base-load time, (c) Rising time, (d) Peak-load time.

Meanwhile, Figure 8 presents the best-fitted curves for power demand during weekends, with the fitted correlations for all time scales summarized in Table 3. Once again, the eighth-degree polynomial fit produces good R^2 values, except for the peak-load time scale. The ranking of R^2 values follows the same pattern as in the weekday case, with the highest for falling time (0.9968), followed by rising time (0.9962), base-load time (0.9566), and the lowest for peak-load time (0.6100). However, compared to the R^2 values obtained for weekdays, the values for all time frames during weekends are lower. This suggests that energy usage patterns on Saturdays and Sundays are more complex and less predictable than those on weekdays.

In this context, the most complex condition occurs during the peak-load time scale, as indicated by the lowest R^2 value of 0.6100 (Figure 8(d)). This characteristic is significantly influenced by the absence of class commitments on the following day (Saturday) and the preceding day (Sunday), allowing for greater variations in lifestyle preferences that impact building power demand compared to weekdays. The model accuracy checks for this time frame showed that the R^2 value improved from 0.6089 (eighth-degree polynomial fit) to 0.6100 (ninth-degree polynomial fit) before slightly decreasing to 0.6098 (tenth-degree polynomial fit). Therefore, the ninth-degree polynomial fit was selected for the peak-load time frame.

Table 2. Proposed weekdays energy modelling base on time scale and time frame.

Time Scale	Time Frame	Power Prediction Correlations	R^2
Falling	12:00 am $\le t <$ 7:10 am	$P_{predict,t} = -1.3047164\ 2762244 \times 10^{-17}(t^8) + 1.99626803\ 97567 \times 10^{-14}(t^7) - 1.21643845\ 507215 \times 10^{-11}(t^6) + 3.82414886\ 370284 \times 10^{-9}(t^5) - 6.87706470\ 268949 \times 10^{--7}(t^4) + 0.00007800\ 6234107446\ 5(t^3) - 0.00506438\ 7964582\ (t^2) - 0.34473366\ 7988075\ (t) + 487.946082\ 830436$	0.9989
Base-load	7:10 am $\le t <$ 5:30 pm	$P_{predict,t} = 3.32154944\ 506944 \times 10^{-18}(t^8) - 2.03438961\ 939639 \times 10^{-14}(t^7) + 5.37344219\ 714283 \times 10^{-11}(t^6) - 7.98645385\ 170079 \times 10^{-8}(t^5) + 0.00007299\ 1953110803\ 6(t^4) - 0.04197761\ 9184977\ (t^3) + 14.8292663\ 744145\ (t^2) - 2942.29924\ 15745\ (t) + 251570.178\ 294604$	0.9802
Rising	5:30 pm $\le t <$ 8:00 pm	$P_{predict,t} = -1.4291828\ 9265555 \times 10^{-13}(t^8) + 1.28055028\ 879975 \times 10^{-9}(t^7) - 5.01795867\ 580609 \times 10^{-6}(t^6) + 0.01123215\ 1645821\ (t^5) - 15.7080511\ 938435\ (t^4) + 14054.1665\ 637341\ (t^3) - 7856179.80\ 869238\ (t^2) + 2508553010\ .08968\ (t) - 3503135425\ 87.02$	0.9978
Peak-load	8:00 pm $\le t <$ 12:00 am	$P_{predict,t} = -2.8343569\ 0289119 \times 10^{-16}(t^8) + 3.14240197\ 613705 \times 10^{-12}(t^7) - 1.51825997\ 323396 \times 10^{-8}(t^6) + 0.00004176\ 7482462604\ 5(t^5) - 0.07157839\ 8436853\ (t^4) + 78.2682891\ 662285\ (t^3) - 53338.9809\ 141409\ (t^2) + 20716853.0\ 098798\ (t) - 3511662213\ .91377$	0.9057

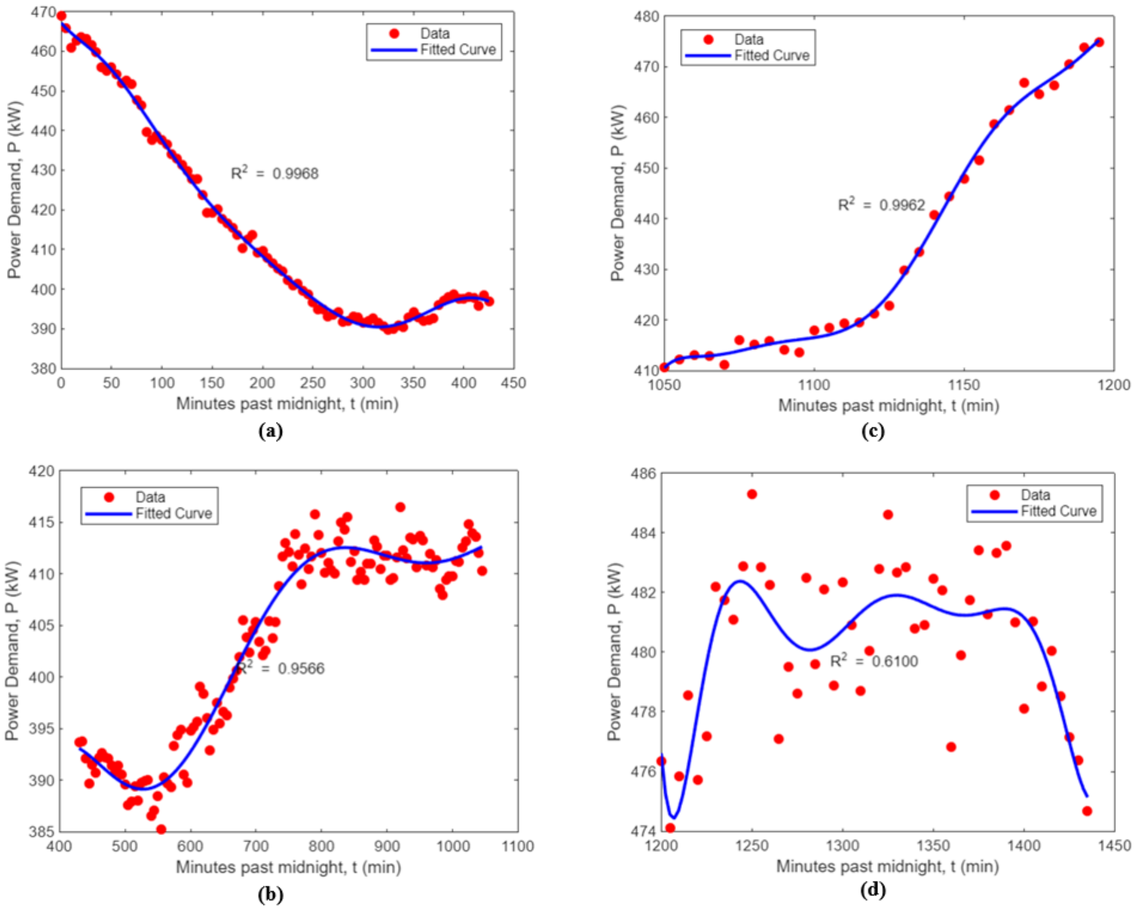


Fig. 8. Power demand correlation prediction base on time scale for weekend. (a) Falling time, (b) Base-load time, (c) Rising time, (d) Peak-load time.

Table 3. Proposed weekend energy modelling base on time scale and time frame.

Time Scale	Time Frame	Power Prediction Correlations	R^2
Falling	12:00 am $\leq t <$ 7:10 am	$P_{predict,t} = 1.54626401\ 168535 \times 10^{-17}(t^8) - 2.76904340\ 496798 \times 10^{-14}(t^7) + 1.99055794\ 834527 \times 10^{-11}(t^6) - 7.33811533\ 441305 \times 10^{-9}(t^5) + 1.46097559\ 508689 \times 10^{-6}(t^4) - 0.00014744\ 8487639705\ (t^3) + 0.00581419\ 4364186\ (t^2) - 0.30115734\ 3885785\ (t) + 467.086233\ 420932$	0.9968
Base-load	7.10 am $\leq t <$ 5:30 pm	$P_{predict,t} = 6.97431569\ 18851 \times 10^{-20}(t^8) - 4.08124891\ 10787110\ ^{-16}(t^7) + 1.00124487\ 13520210\ ^{-12}(t^6) - 1.33186473\ 20351710\ ^{-9}(t^5) + 1.03569503\ 69630810\ ^{-6}(t^4) - 0.00047109\ 3300605177\ (t^3) + 0.11710988\ 1469465\ (t^2) - 12.9176567\ 167766\ (t) + 619.060902\ 90896$	0.9566
Rising	5:30 pm $\leq t <$ 8:00 pm	$P_{predict,t} = -1.0402393\ 5723828 \times 10^{-13}(t^8) + 9.35869517\ 708611 \times 10^{-10}(t^7) - 3.68219712\ 519329 \times 10^{-6}(t^6) + 0.00827546\ 8973411\ (t^5) - 11.6195797\ 051751\ (t^4) + 10437.6032\ 148808\ (t^3) - 5857660.44\ 082816\ (t^2) + 1877772991\ .16222\ (t) - 2632534921\ 21.354$	0.9962
Peak-load	8:00 pm $\leq t <$ 12:00 am	$P_{predict,t} = -7.7362449\ 2059994 \times 10^{-18}(t^9) + 9.50545671\ 197194\mathrm{E}\ -14(t^8) - 5.18360969\ 876822\mathrm{E}\ -10(t^7) + 1.64674558\ 499735\mathrm{E}\ -06(t^6) - 0.00335869\ 6738488\ (t^5) + 4.56116181\ 775393\ (t^4) - 4124.34859\ 545105\ (t^3) + 2394582.67\ 264386\ (t^2) - 810053755.\ 646331\ (t) + 1216521451\ 76.087$	0.6100

3.3 Power Demand Correlation and Power Consumption Prediction Validations

In this validation exercise, actual power demand and energy consumption for selected days in December 2023 were analyzed. Tables 4 and 5 present the predicted values generated by the proposed models for estimating building power demand and energy consumption at various times, *t* and time frames, respectively. The differences between the predicted values and the actual data, measured using a power quality analyzer, are also presented.

Table 4. Power demand validation.

Day/Date	Time	Power (kW)		
		Model Prediction	Actual	% Error
Saturday/9 Dec 2023	7:00 pm (t=1140 min)	437.88	443.69	1.31
Sunday/10 Dec 2023	10:00 pm (t=1320 min)	481.25	479.46	0.37
Monday/ 11 Dec 2023	3:30 am (t=210 min)	405.90	409.35	0.84
Tuesday/12 Dec 2023	2:15 pm (t=855 min)	406.71	388.82	4.60
Wednesday/13 Dec 2023	7:00 pm (t=1140 min)	465.98	456.51	2.07
Thursday/ 14 Dec 2023	10:00 pm (t=1320 min)	488.12	488.18	0.01
Saturday/ 16 Dec 2023	5:50 am (t=350 min)	392.18	392.58	0.10
Sunday/17 Dec 2023	2:00 pm (t=840 min)	412.52	418.74	1.49

Table 5. Energy consumption validation.

Day/Date	Time Frame	Energy Consumption (kWh)		
		Model Prediction	Actual	% Error
Saturday/9 Dec 2023	1 day	10,152.12	10,215.81	0.62
Monday/ 11 Dec 2023	1 day	10,244.58	10,389.22	1.39
Tuesday/ 12 Dec 2023	8.30 am $\leq t \leq$ 4:30 pm	3,155.49	3,088.82	2.16
Wednesday/ 13 Dec 2023	9.00 pm $\leq t \leq$ 11:40 pm	1,311.6	1,351.70	2.97
Sunday/ 17 Dec 2023	5.00 pm $\leq t \leq$ 11:35 pm	3,141.61	3,065.65	2.48

Based on Tables 4 and 5, the maximum errors for power demand and energy consumption estimation are 4.60% and 2.97%, respectively. Additionally, the MAPE values for power demand and energy consumption forecasting are 1.35% and 1.92%, respectively (Figure 9). These values, all below 5%, indicate that the proposed model demonstrates good accuracy in predicting the building's power demand and energy consumption. It is evident that the two independent variables selected for this model development (minutes past midnight and type of day), along with the power-law function approach, are appropriate. However, since the model is developed based on historical data, it is considered model-specific, and its applicability is limited to the building's operational conditions at the time of data collection. As the field data measurement was conducted during the lecture/instructional session when the building was fully occupied, applying this model outside this period such as during semester breaks when occupancy is significantly lower is not valid.

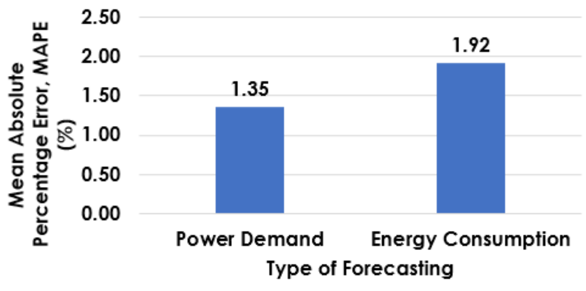


Fig. 9. Mean absolute percentage error of the forecasting model.

4. CONCLUSION

In this study, power demand profile of a student hostel was analyzed, validated and mathematically modeled. The power profile was categorized into four (4) distinct time scales: falling time (12:00 am – 7:10 am), base-load time (7:10 am – 5:30 pm), rising time (5:30 pm – 8:00 pm), and peak-load time (8:00 pm – 12:00 am). The MDs recorded for weekend and weekdays were 515.29 kW (Sunday at 10:05 pm) and 518.47 kW (Thursday at 9:40 pm, respectively. These MDs do not impact the energy cost for the IHL, as the actual MD of the IHL charged by utility provider occurred during office hours (8:00 am to 5:00 pm). Based on this finding, load-shifting strategies are not recommended, as the MD and peak energy consumption of the hostel occur outside office hours, typically during the off-peak period when energy cost under the C1-OPTR tariff is relatively lower than during the on-peak period. However, it is recommended that energy efficiency strategies focus on peak-load times (8:00 pm to 12:00 am) and that weekend energy management be considered due to relatively high base loads.

In the context of the proposed data-driven predictive model, the maximum errors for power demand and energy consumption estimation are 4.60% and 2.97%, respectively. Additionally, the MAPE values for power demand and energy consumption forecasting are 1.35% and 1.92%, respectively. These results demonstrate that modeling across four distinct time scales using two independent variables (minutes past midnight and type of day), along with the power-law function approach, is effective for predicting the power demand and energy consumption of a student hostel. During the model optimization stage, eighth- to ninth-degree polynomial fits were found to provide the best power forecasting performance, achieving R^2 values as high as 0.9989. However, predictions for peak-load periods during weekends were more complex, with an R^2 value of just 0.6100. Compared to previous models proposed by other researchers, the proposed model is relatively simple and does not require extensive or intricate computer simulation programming. However, a key limitation of this data-driven model is that it was developed based on data collected during specific lecture/instructional sessions, limiting its applicability across the entire academic calendar.

In the future, incorporating additional significant parameters along with the integration of machine learning techniques that influence power demand and energy consumption could further enhance the model's accuracy in predicting power demand and energy usage. Factors such as outdoor air temperature, examination days, and a more detailed occupancy rate could be included in future model development. Integrating machine learning into the model would enable a more comprehensive evaluation of various energy consumption scenarios and their potential impact. Consequently, it is also proposed to explore this modeling approach beyond student hostels, such as in commercial and industrial buildings.

In short, the proposed data-driven predictive model can provide quick and accurate information for power demand and energy consumption predictions, towards building energy efficiency improvement and effective energy costs management by optimizing overall energy use. Therefore, it is expected to be valuable for future Demand Response (DR) programs, supporting the analysis of DR initiatives and the optimization of energy efficiency strategies. Indirectly, it can contribute to the environmental sustainability, as now become primary concern around the world.

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