

# AI-Based Connected Load Analysis and Energy Consumption Prediction for Methodist College of Engineering and Technology

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## Abstract

Heterogeneous building functions, changing occupancy, and varied operation schedules determine power consumption, making energy management problematic in university campuses. In order to help Methodist College of Engineering and Technology with their linked load analysis and monthly energy consumption projection, this study presents a viable AI-based methodology. Using a monthly historical energy-consumption series from February 2025 to February 2026 and block-wise connected-load records for six campus blocks, the research integrates engineering load estimate with data-driven modelling. According to the campus's installed load of about 712.14 kW, the most significant demand centers are Blocks E, C, and A, as shown by the connected-load study. Monthly consumption peaked in April 2025 and dropped to a low in December 2025, indicating significant seasonal or operational fluctuation according to the time series study. For shorter-term predictions, we utilise linear regression as a comprehensible baseline, and we apply isolation forest to identify unusual months. The results demonstrate that the framework is capable of locating high-impact load zones, assisting with short-term demand planning, and exposing anomalous months that should be examined by managers. The study finds that structured AI-assisted analysis may improve energy planning at the campus level and provide the groundwork for smart-campus energy management enabled by the internet of things (IoT) in the future, even with a small dataset.

**Keywords:** Energy Management, Campus Energy Forecasting, Machine Learning, Anomaly Detection

## 1. Introduction

One of the most important operating resources for universities nowadays is electricity. Due to the mixed usage of classrooms, offices, workshops, computer labs, lighting systems, and specialist research facilities on campus, engineering colleges in particular have a wide range of electrical demands. Inadequate planning for future infrastructure improvements, unequal load concentration, and needless energy loss might result from a lack of thorough study of such loads.

Methods such as static bill analysis, guesswork, or occasional manual readings are often used in traditional campus energy management. While these methods work well for bookkeeping, they are inadequate for seeing high-load zones, predicting temporary changes, or spotting anomalous activity in real time. On the

other hand, analytics powered by AI can take historical demand data and turn it into diagnostic, descriptive, and predictive insights that administrators can really use.

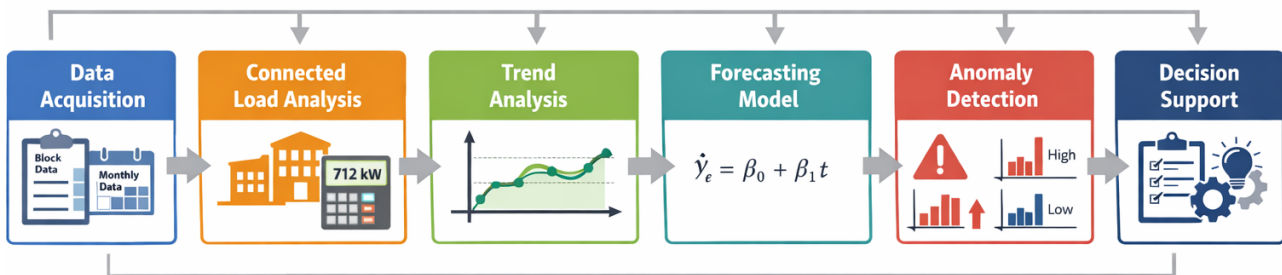


Figure 1. Overall workflow of the proposed AI-based campus energy analytics framework

Data collecting, connected-load modelling, trend analysis, forecasting, anomaly detection, and decision support are all part of the proposed AI-based campus energy analytics framework (Figure 1), which was created by the author based on [1]-[5], [7].

Methodist College of Engineering and Technology is the center of attention in this research. The goal isn't only to compile electrical load data; it's to construct an analytical framework that links installed demand, observed energy usage, forecasting, and fault detection. This paper's solution is to combine interpretable machine-learning technologies with monthly energy statistics and connected-load models.

## 2. Literature Review

Classical time-series techniques gave way to machine learning and hybrid approaches in energy forecasting research. Research on energy forecasting's foundations stresses the need of understanding energy data's trend, noise, and seasonality before choosing a prediction model. Regression, SVMs, neural networks, and hybrid models have all been used to enhance the accuracy of building energy forecasts.

New research in building energy forecasting suggests that data richness is a key factor in determining the best-performing methods. Advanced deep-learning models can be justified by high-frequency sensor streams, but interpretable baselines can prevent overfitting on tiny monthly datasets. Descriptive analytics, predictive analytics, and prescriptive or decision-support analytics are the three primary ways that energy data may be structured, according to the literature on smart-meter analytics [1]-[5], [7].

Identifying anomalies has emerged as a key focus in intelligent energy systems due to the fact that unexpected demand might expose flaws, operational abnormalities, timetable changes, or hidden inefficiencies. Since Isolation Forest can detect outliers in this setting without tagged anomalous samples, it is very applicable. Thus, according to the literature, a single framework should be used to define the campus via connected-load analysis, to estimate short-term demand through forecasting, and to investigate unusual periods through anomaly detection.

## 3. Methodology and Mathematical Modelling

Two supplementary datasets on campus energy use are used in this research. The first piece of data includes electrical information broken down by block for six main campus blocks (A–F). This includes ratings for installed power and statistics for derived energy usage. From 2025 to 2026, the second dataset

records the monthly energy use of the campus. Collecting these statistics allows for investigation of campus energy behaviour in both space and time.

Anomaly identification, data preparation, connected-load modelling, and temporal forecasting are the four primary steps of the process. The monthly and block-wise datasets are cleaned, organised, and made ready for analysis during the data-preparation step. By doing so, we can eliminate formatting problems, make sure that all units are consistent, and compare the installed load to the reported energy consumption directly.

The next step is to calculate the campus's overall electricity consumption using connected-load modelling. By adding together, the installed loads of every single campus block, we can get the total linked load:

$$CL = \sum_{i=1}^n P_i$$

where  $n$  is the total number of blocks taken into account and  $P_i$  is the installed power of block  $i$ . This equation helps to determine the proportional contribution of each block to the overall load and gives a succinct representation of aggregate campus demand.

Here is the fundamental equation for electrical energy:

$$E = P \times t$$

in which the amount of energy used by  $E$  denotes, the power of  $P_i$ , and the operation duration are all shown. For various time horizons including daily, weekly, monthly, and annual operation, this equation is used to match installed power with predicted energy demand.

As a starting point for time-based forecasting, a linear regression model is used. Here is the formula for the forecasting model:

$$\hat{Y}_t = \beta_0 + \beta_1 t$$

where  $\hat{Y}_t$  is the predicted monthly energy consumption at time  $t$ ,  $\beta_0$  is the intercept term, and  $\beta_1$  is the slope coefficient representing the rate of change over time. Here,  $Y_t$  denotes the observed monthly energy consumption, while  $t$  represents the month index. This model is selected because it offers interpretability and provides a suitable baseline for short-term energy forecasting.

To smooth short-term variability and reveal the underlying consumption trend, a three-month rolling average is computed as:

$$RA_t = \frac{Y_t + Y_{t-1} + Y_{t-2}}{3}$$

where  $RA_t$  is the rolling-average value at month  $t$ . By reducing the large monthly swings, this smoothing procedure makes the larger trend in campus energy consumption easier to see.

Lastly, periods of very high or low consumption that do not follow the regular trend may be found using anomaly detection. A systematic framework for analysing campus energy demand and enabling intelligent energy-management choices is provided by the proposed technique, which integrates connected-load analysis, energy modelling, forecasting, and anomaly detection.

#### 4. Dataset Tables and Experimental Results

The electrical dataset used for connected-load estimate and energy contribution analysis is shown in Table 1.

Table 1. Block-wise connected-load and estimated energy dataset.

Block	Power (W)	Hours/day	Daily kWh	Weekly kWh	Monthly kWh	Yearly kWh
Block A	136,327	7	954.289	6680.023	28628.67	348315.485
Block B	95,807	7	670.649	4694.543	20119.47	244786.885
Block C	196,253	7	1373.771	9616.397	41213.13	501426.415
Block D	27,359	7	191.513	1340.591	5745.39	69902.245
Block E	256,200	7	1793.400	12553.800	53802.00	654591.000
Block F	195	7	1.365	9.555	40.95	498.225

Table 2 lists the historical monthly campus energy-consumption series used for time-based modelling.

Month	Month index	Observed energy (kWh)	3-month rolling average
Feb-2025	1	21,958	-
Mar-2025	2	27,970	-
Apr-2025	3	30,740	26889.33
May-2025	4	17,833	25514.33
Jun-2025	5	22,742	23771.67
Jul-2025	6	22,828	21134.33
Aug-2025	7	20,049	21873.00
Sep-2025	8	21,640	21505.67
Oct-2025	9	21,724	21137.67
Nov-2025	10	19,928	21097.33
Dec-2025	11	15,234	18962.00
Jan-2026	12	21,173	18778.33
Feb-2026	13	23,334	19913.67

Table 3 summarises key descriptive statistics and model indicators obtained from the analysis.

Indicator	Value
Total connected load (kW)	712.14
Total monthly block-wise energy (kWh)	149549.61
Total yearly block-wise energy (kWh)	1819520.25
Average monthly historical energy (kWh)	22088.69
Maximum monthly historical energy (kWh)	30740.00
Minimum monthly historical energy (kWh)	15234.00
Linear regression MAE (kWh)	2561.46
Linear regression R <sup>2</sup>	0.211

#### 4.1 Connected-load distribution

The whole load that is linked to the campus is about 712.14 kW. The largest connected load is recorded in Block E, then in Blocks C and A. This concentration suggests that these blocks should be given priority when it comes to energy-saving measures, since these areas would be the most affected by changes made there.

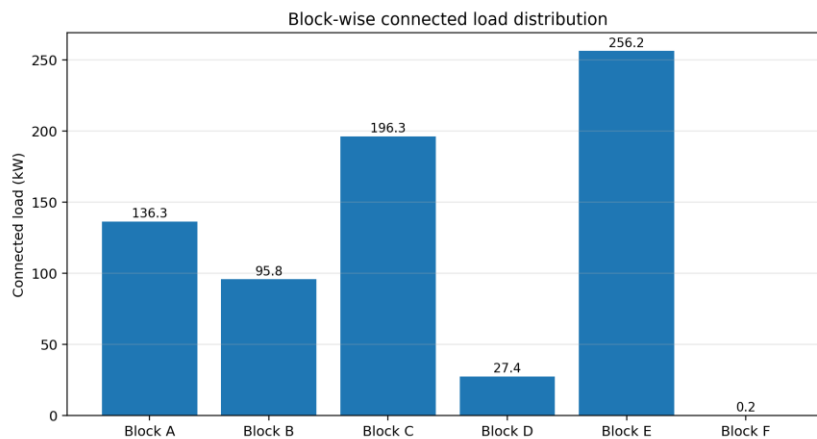


Figure 2. Block-wise connected-load distribution across campus blocks.

The same outcome is supported by the projected monthly energy shares across blocks. In comparison to the other main academic blocks, Block F's projected monthly energy use is minuscule, although Block E's contribution is substantial.

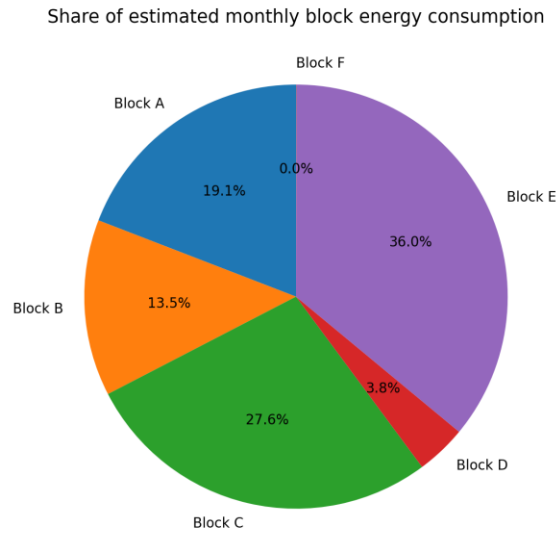


Figure 3. Share of estimated monthly block energy consumption.

#### 4.2 Temporal consumption profile

Variation over time is clearly seen in the historical monthly data. It is reasonable to assume that lower academic activity or vacation schedules are to blame for the fact that demand peaks in April 2025 and hits rock bottom in December 2025. Instead of a strong monotonic trend, the rolling-average curve smooths out the short-term oscillations and shows a mid-range operational band.

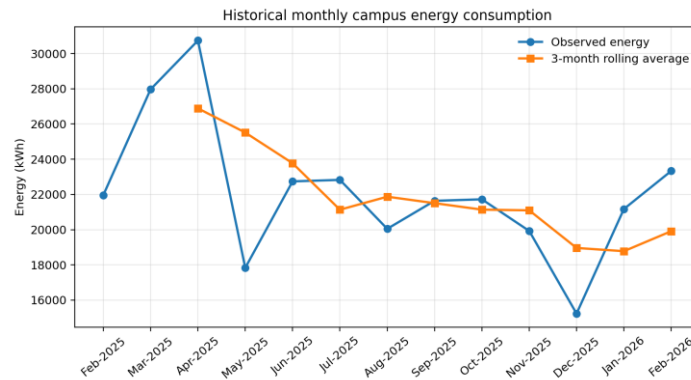


Figure 4. Historical monthly energy use and 3-month rolling average.

#### 4.3 Anomaly detection

A tiny group of months is flagged as aberrant in isolation forest compared to the entire distribution. These months need more investigation because they can point to anomalous laboratory operations, inefficiency, maintenance shutdowns, or odd occupancy circumstances.

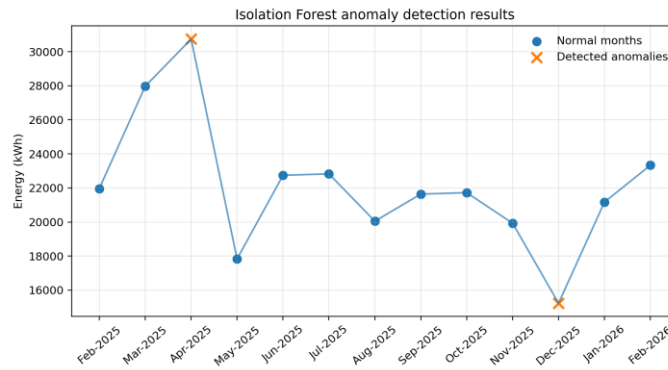


Figure 5. Anomaly detection on the monthly energy-consumption series.

#### 4.4 Forecasting results

For basic, interpretable short-term forecasting, linear regression was used. Although it doesn't account for all regional variations, it gives a clear indication of demand in the near future. The brief duration of the series and the in-sample nature of the reported error necessitate cautious interpretation of the model fit.

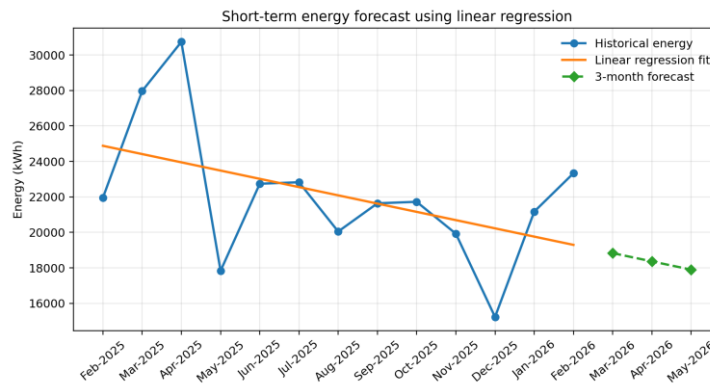


Figure 6. Short-term energy forecast based on linear regression.

Table 4 reports the next three forecasted monthly values generated by the regression model.

Forecast month	Month index	Predicted energy (kWh)
Mar-2026	14	18831.31
Apr-2026	15	18365.97
May-2026	16	17900.63

Table 5 lists the monthly anomaly labels assigned by the Isolation Forest model.

Month	Observed energy (kWh)	Anomaly label
Feb-2025	21,958	Normal
Mar-2025	27,970	Normal
Apr-2025	30,740	Anomaly
May-2025	17,833	Normal

Jun-2025	22,742	Normal
Jul-2025	22,828	Normal
Aug-2025	20,049	Normal
Sep-2025	21,640	Normal
Oct-2025	21,724	Normal
Nov-2025	19,928	Normal
Dec-2025	15,234	Anomaly
Jan-2026	21,173	Normal
Feb-2026	23,334	Normal

## 5. Discussion

Both the geographical concentration and the temporal variability of campus energy consumption are shown by the data. It is more probable that focused intervention, rather than universal control strategies throughout the campus, will be successful since three blocks account for the majority of installed and predicted energy consumption. There are noticeable ups and downs in the monthly series that line up with logical cycles of institutional activity.

From a methodological perspective, the research highlights the need of using interpretable models initially. With linear regression, administrators have a clear baseline to understand and audit. In addition, Isolation Forest may help you identify which periods need an operational review. One model predicts what's likely to happen next, while the other identifies out-of-the-ordinary occurrences, making them a useful decision-support combination.

However, keep in mind that this is just preliminary research. Seasonality, equipment deterioration, and weather-driven variability over longer time periods cannot be adequately captured by monthly data over a single year. Consequently, the campus is anticipated to see future performance increases with the use of higher-frequency metering and the inclusion of explanatory factors like temperature, occupancy, and schedule structure.

## 6. Conclusion

Methodist College of Engineering and Technology implemented a high-quality, campus-wide research framework for linked load analysis and energy consumption prediction using artificial intelligence (AI), as described in this study. In order to measure installed demand, examine consumption trends over time, predict energy usage in the near future, and identify unusual months, the framework integrated engineering calculations with machine-learning techniques.

According to the results, the electrical demand on campus is primarily driven by Block E, then by Blocks C and A, with a combined connected load of about 712.14 kW. April 2025 had the greatest usage and December 2025 the lowest, according to the historical monthly data, which demonstrated considerable

variance in energy use. These results lend credence to the idea that standard energy-control strategies aren't necessary and instead call for tailored block-level management.

After using structured analytics, even a small institutional dataset may become a valuable tool for planning, as shown by the research. Right now, the resultant framework is useful for energy audits, and in the future, it may be extended to smart-campus systems.

## 7. Future Scope

To further identify intra-day peaks and operational fingerprints, future study should include weekly, daily, or fifteen-minute interval metering into the dataset, in addition to monthly observations. Better model accuracy and the ability to prepare based on scenarios would result from adding weather variables, occupancy counts, and equipment-level telemetry.

In the future, as data becomes more abundant, the university may investigate more sophisticated approaches like LSTM networks, gradient boosting, random-forest regression, and ARIMA hybrids. Although these models have the potential to better capture nonlinear interactions, they should only be used when the data is sufficiently large and detailed to warrant them.

An further enhancement involves the implementation of an Internet of Things (IoT) smart energy dashboard. This dashboard will consolidate the institution's meter readings, anomaly warnings, maintenance records, and decision-support outputs into a single operational interface.

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