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REAL TIME ENERGY CONSUMPTION MONITORING AND PREDICTION FOR UNIVERSITY CAMPUS

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Abstract

The real time energy consumption monitoring system at the various buildings of university campus is quite necessary task for efficient use of energy. Such monitoring system helps to understand the proper behavior of consumers and ultimately, load demand patterns of various buildings. In this regard, a real-time energy monitoring system has been implemented at Kathmandu University. The system comprises six smart meters installed in university buildings at major energy consumption points to obtain high-resolution data on energy usage. Robust energy prediction models have been developed by combining electricity consumption data with weather information, including academic holidays. The prediction performance of the models is examined using evaluation metrics such as the root mean square error (RMSE) and execution time. A mobile application and web dashboard have also been developed to visualize the results and provide feedback to consumers and utility providers. This visualization dashboard provides real-time information, identifies energy consumption patterns, potential overloads, and ultimately supports consumers in optimizing their electricity usage.

Keywords: Smart meter, Load profile, Machine learning, Load forecasting, Energy monitoring

1. INTRODUCTION

Inefficient use of energy and energy wastage are contributing to energy crises in most regions (Cui et al., 2014). The efficient use of electricity to enhance energy efficiency and sustainable goals has become a popular research topic in recent years. Developed countries have focused on this improvement in energy efficiency rather than increasing the overall energy production capacity. Consumers in developing countries still need to be educated about the active measures required to improve energy efficiency by reducing energy wastage (Akhtar et al., 2020).

Energy monitoring systems have become a very important tool to achieve energy efficiency. An energy monitoring system refers to an automated system for collecting energy information data, analyzing it, and providing the information in a user-friendly way. Monitoring the load on the consumer side has become more convenient due to advancements in communication and data transmission technologies (Dat et al., 2023). The use of Internet of Things (IoT)-based energy monitoring devices like smart meters and sensors makes it possible to collect real-time energy consumption data and also transmit data to distant locations through the Internet. The structure of a smart meter-based energy monitoring system is shown in Figure 1 .The system comprises three different layers.

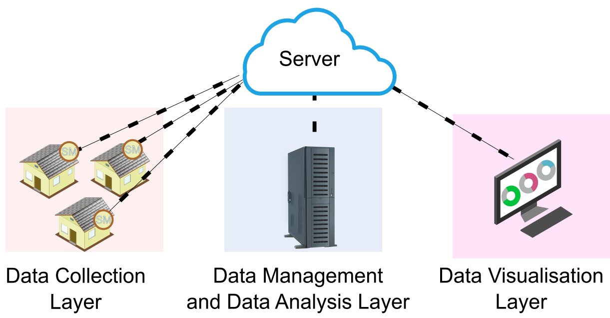

Figure 1. Layers in energy monitoring system

The data collection layer consists of smart meters installed at consumer premises. The layer is responsible for monitoring electricity consumption data at a small granular level. The measured data is transmitted to a remote server on a timely basis. Communication is done using the

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message queuing telemetry transport (MQTT) protocol over a Wi-Fi network at a resolution of one minute.

The data management and data analysis layer consists of a cloud computing infrastructure. The cloud computing infrastructure provides two major components: a data storage component and a data analysis component. The data storage component is responsible for storing the energy consumption data. The data analysis component is responsible for analyzing the stored data. Analytics is known as the scientific process of transforming data into insights for making better decisions. It is commonly dissected into three stages: descriptive analytics (what do the data look like), predictive analytics (what is going to happen), and prescriptive analytics (what can be) (Zhang et al., 2020).

The result obtained from load analysis is represented in an easily understandable way through the data visualization layer. Representing the results in the form of graphs and plots is significant for understanding the load and performing energy management actions. The choice of the most appropriate visualization depends on factors such as data source and availability, goals of the energy analysis, and target user (Vera-Piazzini et al., 2023).

1.1. Mobile Application-based Energy System

The energy consumption pattern of a building is associated with the behavior of the consumer. Providing valuable insights to consumers regarding their electricity consumption patterns leads to effective management of electricity. A simple system is implemented with the help of a mobile application. The application serves as a user feedback system for user awareness, encourages savings, and reduces usage during peak times. Suggesting users set energy saving goals, comparing consumption data, getting energy saving tips, or providing warnings for upcoming energy peaks (Nguyen, 2014).

1.2. Load Forecasting Model

Load forecasting is the process of predicting the future electricity demand with the help of historical data. Accurate load forecasting is significant for the management and optimization of electricity consumption within university campuses. The major applications of forecasting include energy cost optimization, efficient operation of the load, infrastructure planning and maintenance, integration of renewable energy sources, and peak load management. The forecasting horizon may range from a few minutes to several years, depending on the specific application. Based on the time horizon, load forecasting can be categorized based on the time horizon into very short-term load forecasting (VSTLF), short-term load forecasting (STLF), medium-term load forecasting (MTLF), and long-term load forecasting (LTLF). VSTLF and STLF can have an immediate impact on a building's operation and scheduling and are crucial components for building energy management systems. MTLF and LTLF forecasting have greater importance for longer-term planning (Yildiz et al., 2017). Various applications of forecasting, along with their respective time horizons, are illustrated in Figure 2.

Two different forecasting approaches are used for predicting the energy consumption of a building: statistical and machine learning-based approaches. In (Sherpa et al., 2023), the load forecasting of a university campus is performed using various statistical methods. The major limitations of statistical models, such as ARMA and ARIMAX, are their assumptions that the input time-series data must exhibit stationarity of the dataset. This poses a significant challenge while building the model with low and highly variable loads, such as university campuses, where consumption patterns can fluctuate drastically. The statistical models also struggle to capture sudden changes or events, such as unexpected campus closures, spikes in load during events, or irregular occupancy patterns. Therefore, artificial intelligence (AI) based machine learning (ML) techniques are considered for this study, as ML methods have played a significant role in advancing the field of energy forecasting (Chen et al., 2004). The widespread adoption of smart meters and the availability of low-resolution data make ML models for forecasting at the building level more feasible (Haben et al., 2023). The increasing interest in AI/ML methods has been fueled by rapid advancements in computing power. Advanced algorithms for deep learning (Shi et al., 2017), reinforcement learning (Feng et al., 2020), and transfer learning (Cai et al., 2020) are being increasingly adopted in energy applications. However, due to limited data (less than a year), only ML algorithms are considered.

1.2.1 Linear Regression Model

$$\hat{y} = w^T x + b \tag{1}$$

where:

- $\hat{y}$ is the predicted (forecasted) value,

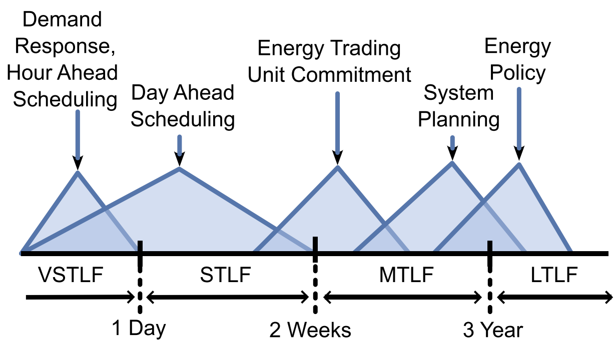

Figure 2. Load forecasting applications and classification

- $x \in \mathbb{R}^n$ denotes the input feature vector,
- $w \in \mathbb{R}^n$ is the weight vector (slope),
- $b \in \mathbb{R}$ is the bias (intercept) term.

The parameters w and b are obtained by solving the following optimization problem:

$$\min_{w,b} \left\{ \frac{1}{2m} \sum_{i=1}^{m} (\hat{y}_i - y_i)^2 \right\} \tag{2}$$

where m is the number of training inputs

1.2.2 Support Vector Regression (SVR) for Machine Learning

$$\hat{y} = w^T x + b \tag{3}$$

where:

- $\hat{y}$ is the predicted (forecasted) value,
- $x \in \mathbb{R}^n$ denotes the input feature vector,
- $w \in \mathbb{R}^n$ is the weight vector (slope),
- $b \in \mathbb{R}$ is the bias (intercept) term.

The parameters w and b are obtained by solving the following optimization problem:

$$\min_{w,b} \left\{ \frac{1}{2} w^T K w + C \sum_{i=1}^{n} L_\varepsilon(y_i, \hat{y}_i) \right\} \tag{4}$$

where:

- K is the kernel matrix that maps the input data into a higher-dimensional feature space,
- $C > 0$ is a regularization hyperparameter that controls the trade-off between model complexity and training error,
- $L_\varepsilon(y_i, \hat{y}_i)$ is the ε-insensitive loss function defined as:

$$L_\varepsilon(y_i, \hat{y}_i) = \max(0, |y_i - \hat{y}_i| - \varepsilon) \tag{5}$$

Here, ε is a predefined threshold within which no penalty is imposed for prediction errors.

1.2.3 Decision Tree Regression

$$f_p = \sum_{p=1}^{P} \alpha_p \chi_p(\boldsymbol{X}) \tag{6}$$

where:

- χ_p is a characteristic function defined by

$$\chi_p(\boldsymbol{X}) = \begin{cases} 1, & \textit{if } \boldsymbol{X} \textit{ is in set } C_p \\ 0, & \textit{otherwise} \end{cases}$$

- $\alpha_p = \frac{1}{N_p} \sum_{t=1}^{N} L_t \chi_p(\boldsymbol{X}_t)$ is the average of the dependent variables L_t where the corresponding independent variables $\boldsymbol{X}_t$ are within the partial set C_p.
- P is the number of disjoint sets of $\boldsymbol{X}$
- $p = 1, 2, 3, \ldots, P$
- C_p is the disjoint subset of $\boldsymbol{X}$
- N_p is the number of points in the set C_p
- L_t is the observation (dependent variable) at time t

1.2.4 Artificial Neural Network for Regression

$$\hat{L}_{N+1} = h(x) = g\left(\sum_{k=1}^{n} \beta_k X_{k,N+1}\right) \tag{7}$$

where:

- g is the activation function
- n is the number of input variables
- L_t is the load at time t
- $X_{1,t}, \ldots, X_{n,t}$ are the input variables at time t
- β_k is the weight of a neuron

1.3. Contribution of This Paper

The major contribution of this paper includes

1. Deployment of smart meters across various buildings within the university campus for real-time energy monitoring.
2. Analysis of energy consumption patterns using smart meter data.
3. Development of machine learning models for short-term and medium-term electrical load forecasting.

4. Implementation of a mobile and web-based application for intuitive visualization and monitoring of energy usage trends.

The remainder of this paper is organized as follows. Section 2 describes the overall methods, including data acquisition, data processing, forecasting, and visualization. Section 3 presents the result. Section 4 concludes this paper.

2. Methodology

The detailed methodology involved in the study is shown in Figure 3. The core steps include data acquisition, preprocessing, forecasting, and energy price calculation, followed by the development of a mobile and web-based platform for real-time energy insights.

2.1. Data Acquisition

The raw input data for the analysis comprises

1. Smart meter data: collected from seven different locations within Kathmandu University and stored in comma-separated values (CSV) format.
2. Ambient temperature: Sourced from the Solcast API Toolkit, featuring a temporal resolution of five minutes.
3. Holiday Schedule: Extracted from the academic calendar of Kathmandu University.

2.2. Data Preprocessing

The raw datasets were cleaned, synchronized, and merged into a unified structured format using Python. Standard preprocessing techniques such as missing data imputation, time resampling, and feature engineering (e.g., encoding holiday indicators, aggregating temperature averages) were applied to prepare the data for modeling.

2.3. Forecasting and Energy Price Calculation

The core focus of this study lies in predictive modeling and price estimation.

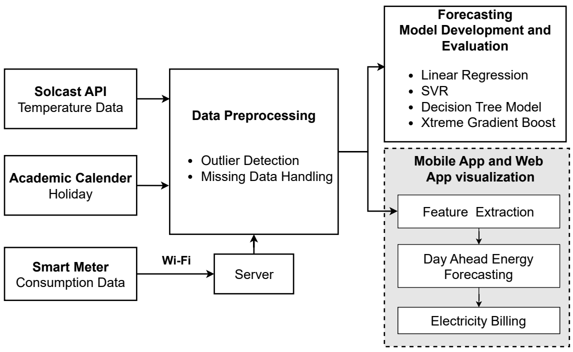

Figure 3. Methodology

Forecasting Energy Demand:

Multiple machine learning based forecasting models were used to predict future energy consumption. The forecasting model includes multiple input features and a single target variable. The input feature includes the past three days usages data, temperature data, holiday data and the months. A total of 11653 data from August to November 2024 was taken as training data, whereas 2881 data from the month of December 2024 was taken as testing data. In order to speed up the simulation the the Z score normalization was used. Table 1 summarises the various models used for forecasting along with their performance metrics. The performance metrics includes the root mean squared error (RMSE) and execution time.

Energy Price Calculation: The electricity billing was performed according to the Time-of-Day (ToD) tariff structure implemented by the Nepal Electricity Authority (NEA). Under this system, different tariff rates are applied based on the time period: peak hours, normal hours, and off-peak hours. This allows users to view detailed billing information according to each ToD period. Understanding how much energy is consumed during peak, normal, and off-peak hours helps consumers identify opportunities to reduce electricity costs by shifting load (e.g., running heavy appliances during off-peak periods). Integrating the cost calculation in a mobile app enables consumers to simulate potential savings opportunities by adjusting consumption patterns across different ToD periods and receive personalized recommendations for energy cost optimization based on ToD rates.

2.4. Visualisation and Deployment

Descriptive analytics were performed using Python libraries such as Matplotlib and Seaborn to visualize consumption patterns, peak demand periods, and user-specific profiles.

A user-friendly mobile application and web dashboard were developed to deliver real-time insights. Consumers can monitor their energy consumption and projected bills and receive customized suggestions for reducing peak load usage. The platform aims to empower users with actionable data, promoting energy-efficient behaviors and strategic energy cost management.

3. Results

The predictive and descriptive analysis of transformer data is presented in this section.

Time series plots in Figure 4 show the variation in electricity usage from the month of August to December of 2024. Electricity usage varies from a minimum of 5 kWh to a maximum of 70 kWh. Electricity consumption patterns are almost similar in the months of August and September, with peak demand being around 40 kWh. This peak demand fell by 50% in the month of October. A rapid surge in electricity demand was seen in November and December, with peak demand recorded at 70 kWh in the second week of December. From the second week of December, a slow decrement in energy consumption can be seen.

Figure 5 shows the variation of daily energy consumption from the month of August to December 2024. A minimum of 1000 kWh of energy is required for the operation of the building. Daily energy consumption is around 2000 kWh in the months of August and September. In October, daily energy consumption varies between 1000 and 1500 kWh. The daily energy consumption for the month of December became twice that of August and September.

Figure 6 shows the energy consumption of a single week from 9th August to 15th August, 2024. The 10th of August is a Saturday (i.e., an academic holiday)

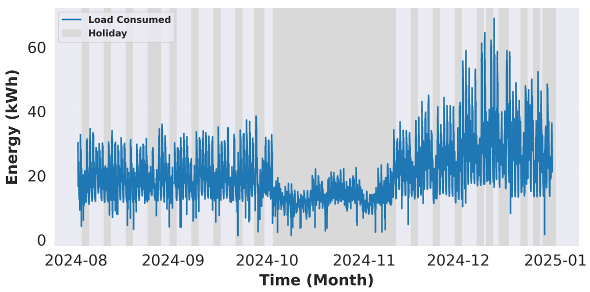

Figure 4. Full timeseries visualization of smart meter data

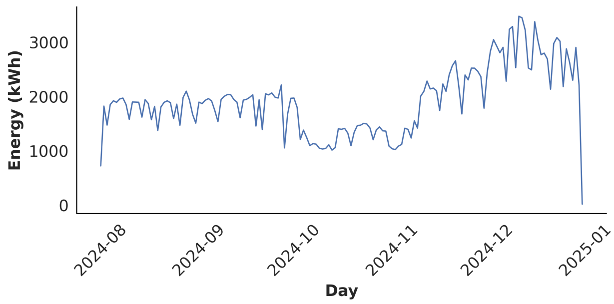

Figure 5. Total daily consumption

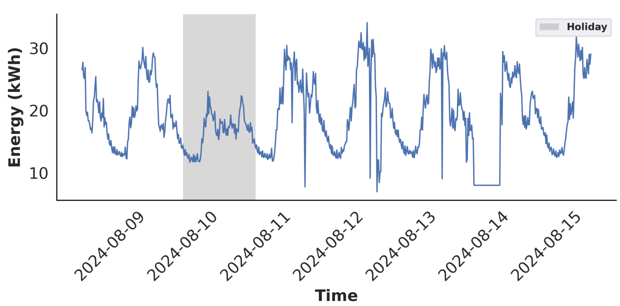

Figure 6. Energy consumption from 9th to 15th August, 2024

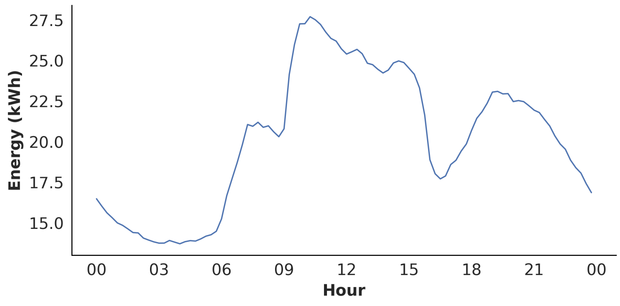

Figure 7. Daily load curve

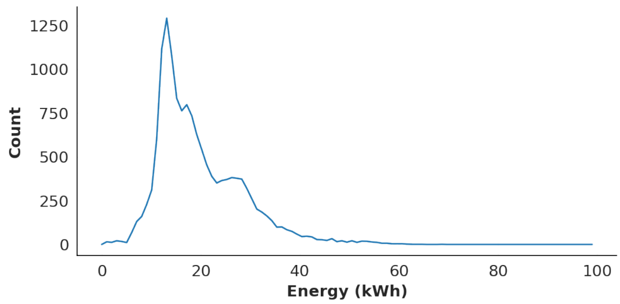

Figure 8. Histogram of energy consumption

indicated with a grey background in the figure. The energy consumption pattern follows a similar repeated pattern for non-academic days. The peak energy consumption during the holiday is two-thirds of the peak energy consumption for non-academic days.

Figure 7 shows the daily load curve. The mean energy consumption for five-month intervals can be seen in this curve. The load curve follows a bimodal distribution with two distinct peaks. The morning peak is seen around 10:00, and the evening peak falls around 19:00. The morning peak is about 25% larger than the evening peak.

Figure 8 shows the distribution of the energy profile. This curve shows information on how often and how much energy is consumed. The curve shows three peaks, indicating there are 3 different appliances whose power

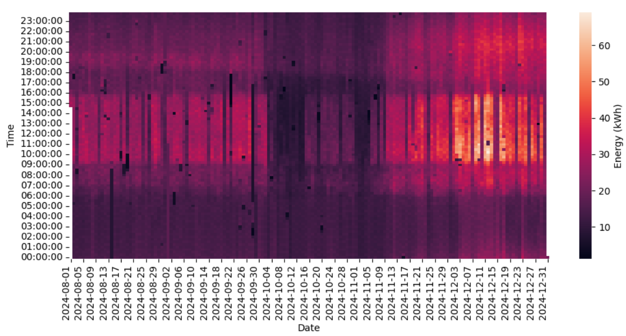

Figure 9. Heatmap of energy consumption

Table 1. Comparison between Various Forecasting Models

Methods	Execution Time (sec)	RMSE (kW)
Linear Regression	0.03	0.88
SVR Model	6.61	0.87
Decision Tree Model	0.11	0.95
ANN Model	**10.78**	**0.70**

consumption is significantly different from others and are used more frequently than others.

Multidimensional charts, such as the heatmap shown in Figure 9, are useful in observing energy consumption over a larger period of time. The x-axis of the plot shows the date in chronological order from left to right, and the y-axis shows the time of day in chronological order from bottom to top. Each pixel in the plot represents a particular date and time. The color of each pixel indicates how much energy is consumed at a particular date and time. Brighter pixel color represents higher energy consumption, and a darker pixel represents lower energy consumption. The plot shows energy consumption is higher between 9:00 and 16:00. The energy consumption for the month of October is lower compared to other months. Darker scatter pixels in the plot are due to the outage of electricity.

Figure 10, Figure 11, Figure 12 and Figure 13 presents the comparison between the actual and forecasted

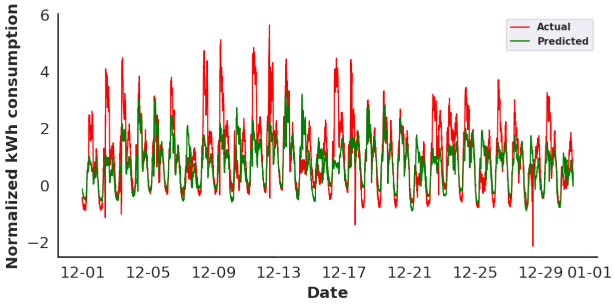

Figure 10. Linear regression forecasting model

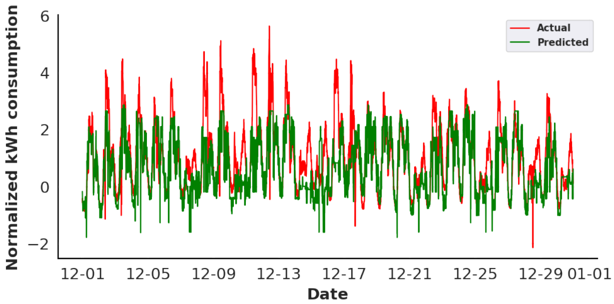

Figure 11. Decision tree model

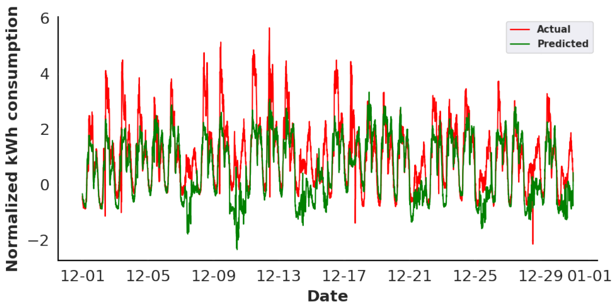

Figure 12. ANN model

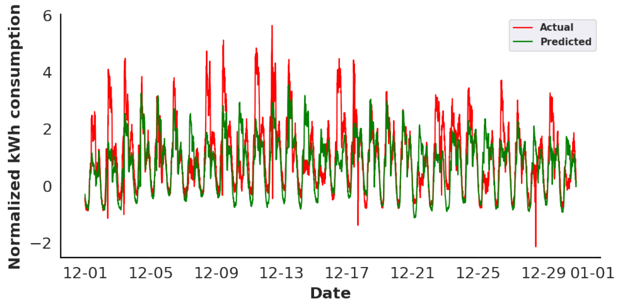

Figure 13. SVR model

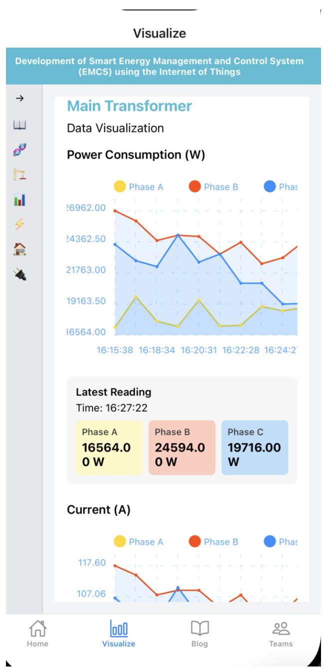

Figure 14. User Friendly mobile app for real time consumption monitoring

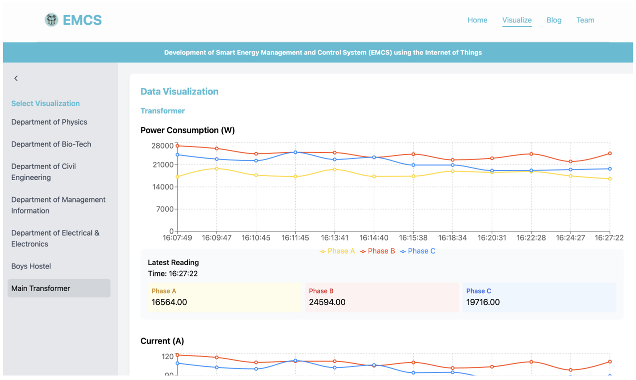

Figure 15. User friendly web dashboard for real time consumption monitoring

energy consumption for the month of December. Actual energy consumption is shown by the red curve, and predicted energy consumption is shown by the green line. All the model were trained and tested on Google Colaboratory using the default runtime environment. A comparison between various models is presented in Table 1. Performance is evaluated in terms of execution time and RMSE matrices. The ANN model outperforms the other models in terms of RMSE. However, the ANN model takes significant time for better accuracy.

A developed mobile app and a web dashboard, as shown in Figure 14 and Figure 15, provide information regarding energy consumption, consumption patterns, and potential electricity saving opportunities in a simple, user-friendly approach. The app uses the historical consumption data to suggest the possible size of photovoltaics, along with the annual energy cost savings, the investment cost required, and the possible payback period. The app can also help users calculate the possible cost-saving opportunity they can achieve through shifting the load to avoid peak-time tariffs.

4. Conclusion

In this study, IoT-based real-time energy monitoring system is implemented for the university campus. The system includes six smart meters installed at major energy consumption points to collect high-resolution usage data. The energy consumption in winter is 75% higher than that of summer. This increment is due to the use of increased electricity usage for heating purposes in winter. Energy consumption during long vacations falls to the lowest. The absence of academic activities and fewer people in the hostel contributed to this reduction. The load curve shows two peaks, one in the morning and one in the evening. The larger morning peak corresponds to the time of the start of academic activities, and the evening peak corresponds to the time of dinner. For academic days, the daily load curve shows the same repetitive pattern indicating repetitive scheduled actions. The heat map is suitable for showing electricity usage patterns over a long range. The information such as high electricity usage during office hour, higher consumption in winter and lower consumption in vacation and winter can be visualized through a single graph. Various machine learning based model were used for load prediction. Various machine learning model shows varying accuracy and execution time. Accurate load forecasting can be used in load management, effective energy management system and taking various demand response action. The development of mobile apps and web dashboards provides real-time visual feedback, helping users recognize consumption patterns, detect overloads, and optimize electricity use. The findings of this study are consistent with existing literature on building-level electricity consumption analysis and forecasting. Past work, such as (Brudermueller and Kreft, 2023), focused primarily on descriptive analysis of building energy usage. This study extends those efforts by incorporating multiple load forecasting models and evaluating their predictive performance. In addition, the development of a mobile application for user-friendly monitoring enhances the practical applicability of the proposed approach.

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