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Design and Development IoT based Smart Energy Management Systems in Buildings through LoRa Communication Protocol

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Abstract:
Energy management is a vital tool for reducing significant supply-side deficits and increasing the efficiency of power generation. The present energy system standard emphasizes lowering the total cost of power without limiting consumption by opting to lower electricity use during peak hours. The previous problem necessitates the development and growth of a flexible and mobile technology that meets the needs of a wide variety of customers while preserving the general energy balance. In order to replace a partial load decrease in a controlled manner, smart energy management systems are designed, according to the preferences of the user, for the situation of a full power loss in a particular region. Smart Energy Management Systems incorporate cost-optimization methods based on human satisfaction with sense input features and time of utilization. In addition to developing an Internet of Things (IoT) for data storage and analytics, reliable LoRa connectivity for residential area networks is also developed. The proposed method is named as LoRa_bidirectional gated recurrent neural network (LoRa_ BiGNN) model which achieves 0.11 and 0.13 of MAE, 0.21 and 0.23 of RMSE, 0.34 and 0.23 of MAPE for heating and cooling loads.

Keywords-Smart energy management, buildings, LoRa communication, data prediction, neural networks.

I. Introduction

The Internet of Things (IoT) is applicable in several sectors, including transit [1], healthcare [2], agribusiness [3], and electricity networks [4]. These IoT solutions seek to watch and manage many components and gadgets in a variety of situations to streamline duties and offer practical uses for everyday life [5]. Energy is a key component of the electric power infrastructure that powers our houses and equipment. But since determining a home's usage relies heavily on an electronic energy meter, utility companies must hire staff to carry out the necessary measuring duties each month in order to charge their clients [6]. Regarding device utilization inside a home, occupants might not be conscious of the specific power requirements for each appliance, leading to unknowingly wasteful energy usage. India has a target of installing 6.5 million smart meters by 2025 [7] in this respect. The major objective of this work is to employ smart meters to reduce energy usage by introducing new tariff structures, offering more comprehensive energy invoicing, and using displays through online interfaces and mobile apps.

The Internet of Energy, smart networks, and smart houses are just a few of the energy saving methods that the IoT will be crucial in allowing. This is made possible by the use of digital sensing and communication tools that enable a home energy management system (HEMS), which supports contact between the utility and the power infrastructure while allowing constant usage tracking and gadget control [8]. Data is collected through IoT devices and then sent to a cloud-based system architecture for analysis and storage [9]. The main components that may be designed and implemented in cloud-based infrastructure to meet the IoT cloud-based needs for a range of energy Internet apps are databases, file storage systems, and data-driven applications. The tasks are becoming more and more alluring to research institutions utilising the technologies that are now being developed when it comes to the construction of sensor networks [10]. The problem of electricity usage is growing at the same moment. The power source will last for months, years, or even decades when a network of devices is created. As a result, the issue of efficient energy management is one of reality, attracting the complete attention of both the scholarly and business communities.

Harvesting natural energy from the surrounding world is one way to make wireless sensing nodes more energy-efficient [11]. Many energy gathering sources of sustainable energy, such as thermal mechanical from the shaking of piezoelectric devices [12], solar sources [9], [10], sound wind, or energy generated from ocean waves [13], can be found in scientific study articles. These sources can be used

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to fuel portable instruments. Depending on utilization or natural factors, each of these sources has a certain quantity of energy it can generate, but solar energy is the most widely available and plentiful green energy source and is used by many WSNs.

The Internet of Things (IoT) environment, which uses battery-powered devices, suffers as a result of these current surges because they shorten the lifespan of traditional power sources.

Following are the primary input and uniqueness of this work:

- To design, build, and test a novel power management framework built on an effective energy storage system for end-node devices that can be combined with a LoRaWAN communication system.
- The suggested SEMS is linked with the IoT ecosystem to enable distant surveillance and additional data analyses.
- Creating and implementing a three-layer HEMS design that enables the collection and storage of data on energy usage from home's primary load and utilities.
- Here, the prediction of data is done by bidirectional gated recurrent neural network (BiGNN) model based on finding a time series forecasting solution for the entire hourly power usage with numerous delays.
- Additionally, the suggested smart energy management system may be used to maximize the usage of electricity produced by independent systems like solar energy, wind energy, etc.

In rest of the article is summarized as below. In section 2, the earlier smart energy management with LoRa communication and efficient data prediction model are provided. In section 3, the proposed intelligent energy management system for buildings with LoRa communication protocol and neural network based data prediction models is detailed. In section 4 the results are analysed by comparing with existing methods. Finally in the section 5 the conclusion and the future move are given.

II. Related works

Each utility follows its preferred levels for the end of power disruptions. The energy usage pattern is altered to off-peak times in order to better the power quality, making sure that each affected area gets the fewest possible outages. To address the problem of total outages, a significant amount of research has focused on the development of Intelligent Power Managing Services (IPMS) among clients that are beneficial to both enterprises and residential users [14]. It is now possible to maximize power use at the point of intake to get a better handle on the resources provided, thanks to the increased emphasis on energy tracking devices [15]. By maximizing customer satisfaction while consuming the least amount of power feasible, the SP-MSS's primary goal is to balance the supply and demand of energy. Energy saving during high utilization periods is subject to a number of restrictions [16].

The gadget can usually be split into two categories: those that can be scheduled and those that cannot. The type of such expandable processing hardware can also be non-interruptible or uninterruptible [17]. Dishwashers and pool machines, for instance, may both be schedulable, time-limited, and non-interruptible machinery [18]. The quantity of energy used by warming, cooling, and ventilation ducts along with other temperature equipment relies on the local environment. However, data from air temperature sensors can actually contribute more to effectively organizing and minimizing the use of conventinal energy. So there is no automated mechanism to control how the device works.

In [19] assessed the effectiveness of an EMS system before and during implementation by looking at energy usage data, temperature differential, room temperature, and client usage trends. According to accounts, significant power savings can be achieved by changing TV utilization habits, reducing inactive energy use, and modifying freezer limits in accordance with the prior limitations. The PSO Algorithm scheduler was suggested by the writers as a better strategy that concentrates on reducing power expenses and high traffic utilization for a customer [20]. Additionally, authors used a real timing system that gave devices priority in order to travel for the longest possible period while using a great deal less energy.

The authors present a multi-agent-based comfort energy planning system [21]. This allows the deployment of the regulating processes while accounting for occupants and sense input data. It collaborates with building inhabitants using real information like actual room temperature, utilization habits, and user procedures to guarantee comfort conditions and thereby reduce power consumption. Developed a database containing statistics on evolving energy values and detection reactions [22]. Another goal is to create a reliable energy efficiency ranking using a criteria-set-based clever system that integrates technological knowledge in order to handle energy operations while also keeping client satisfy and reducing electricity costs. The author offers a uniform system to control devices in a business structure (i.e., heating, cooling, and air conditioning) in order to guarantee individual customer satisfaction while taking their tastes into consideration [23].

The majority of power management strategies mentioned in the study mainly serve domestic users and are designed to schedule the operation of equipment according to preset priorities [24]. Therefore, the gadget choices change from time to time based on the user's convenience and natural considerations. The potential to enhance the power

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management mechanism is thus given by this research. It contains cost-saving techniques, a priority feature that the user may choose, and is flexible enough to support a variety of users without sacrificing comfort levels [25]. Improved self-diagnostic capabilities for trustworthy connection and straightforward scalability just at the device layer are also taken into consideration by the SP-MSS architecture. Throughout this research, the suggested SP-MSS is also connected to the IoT environment for extra data processing and monitoring purposes. The hardware display of prototypes is developed in a lab environment, where testing is done while considering the ToU& sensor, as well as other adjustable priority levels and demand restriction constraints [26].

[27] presents an intelligent irrigation system which integrates a data integration model with a long-range (LoRa) network in order to improve the watering schedule. A data fusion model that integrates data from several heterogeneous sources, such as historical weather data, user irrigation records, weather projections, and data from online monitoring devices, is suggested. Recurrent Trend Predictive Neural Network based Forecast Embedded Scheduling (rTPNN-FES), a sophisticated machine learning method, is suggested in [28] as a means of effectively controlling domestic demand. An innovative neural network design called rTPNN-FES predicts green energy production while also scheduling home utilities. The integrated structure of rTPNN-FES prevents the use of distinct forecasting and scheduling algorithms and creates a plan that is resistant to forecasting mistakes. The majority of energy management systems covered in the literature are mostly targeted at residential users and created to plan appliance operations based on Utility signals assigned with set priority criteria. A portable, adaptable energy management system that may be used by a variety of users and has reliable communication and capable of managing power-intensive loads is still needed in order to lower overall electricity costs and reduce peak household demand without significantly affecting user satisfaction.

III. System model

Figure 1 illustrates the web-enabled Smart Grid (SG) design, which is made up of IoT devices on top of web services. It uses both sustainable and non-renewable energy sources, both of which are linked to computerized energy meters.

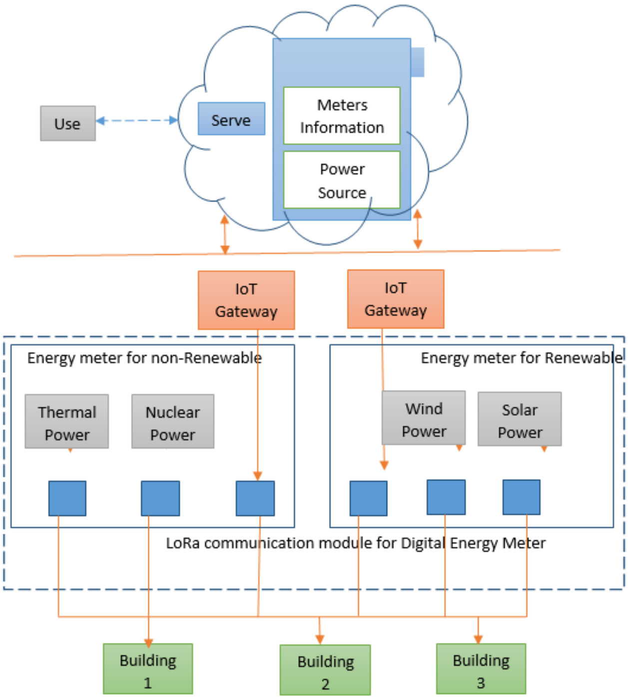

Figure 1. Block Diagram for Proposed Method

Data on domestic energy usage is gathered by digital energy meters, and it is further gathered by IoT interfaces so they can connect to the computer hosting the online services. Individual computerized energy meters are linked to each energy source in this design. Data on home energy usage is gathered by these computerized energy meters. Different IoT points that routinely interact with these meters gather the data from energy meters for non-renewable and green sources. IoT gateway data is regularly updated on the computer, which then offers online services on top of these IoT devices. The addresses of the homes linked through the SG as well as meter data are included in these online services.

Additionally, online services are made available for each house for the ordering of power sources and the management of the energy sources by directly swapping the source managers using IoT devices. A person can receive these services by linking to any computer over the Internet. Each household's energy sources are shifted using source shifters that are managed by IoT devices; these IoT devices switch the energy sources in response to commands from the user received through the server.

3.1 Architecture of SEM gateway

SEM Gateway (Central controller): A power negotiation algorithm that serves as the SEM system's brain is used in this instance as the SEM's principal control unit. Between the Utility and the client, the SEM acts as an agent. It makes the decision of whether to switch ON or OFF a particular group of end-user appliances based on the utility signal it receives and the homeowner's load priority choices. In order to avoid excessive tariff expenses, the SEM unit warns the user when turning on a high power-consuming device during peak load hours. It also has the responsibility of collecting data on energy usage from all load controllers using LoRa modules, providing homeowners with an LCD interface via which they can view real-time energy consumption statistics, and setting an appliance's priority based on their requirements.

SEM communication module: The coordinator (user end) and a router (appliance end) module establish wireless connection. In this case, the communication module is an XBee Series- 2 device, and the SEM system's internal communication is made possible by attaching a LoRa module at each end. A load controller's LoRa module is set up as a router (appliance end) and a coordinator (second module). (user end). Once communication has been established between the coordinator and router inside the SEM system, the SEM unit uses the data on power consumption that has been gathered to run the power negotiation algorithm, and the coordinator connected to it transmits the controls signals to the router.

3.2 Architecture of SSM (Load controller)

Through the use of a Smart Socket Module, a load driver acts as a link between the SEM device and a particular utility.(SSM). It offers fundamental battery control features. (i.e., control, communicate).

- A data collection and processing module: The primary job is to gather real-time electrical metrics, including RMS voltage and current values, and to further calculate an appliance's perceived power, actual power, energy, and power factor. Here, voltage and current are measured using LEM devices that are founded on the Hall effect.
- A control module: In accordance with instructions given by the SEM Gateway, it is an electrical relay circuit that is used to turn a specific device ON or OFF.
  - Communication module: It creates a two-way communication channel between the SEM Gateway and a Smart Socket Module. A load manager receives instructions from a SEM device and transmits the data it has gathered about power usage to the SEM Gateway. The SEM unit collects data from each load controller, runs the winning algorithm, and sends control commands to each load controller.

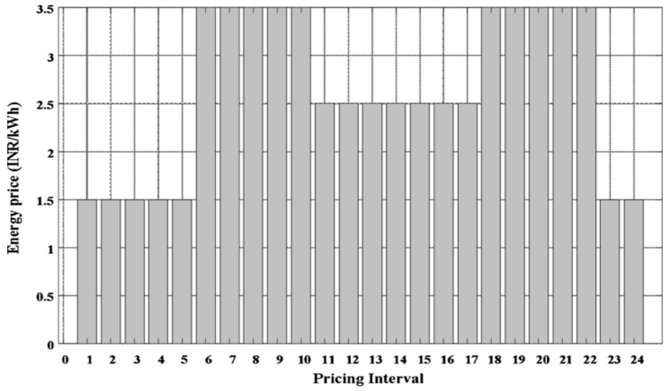

Figure 2 (a) Approved ToU Tariff for Consumers [30]

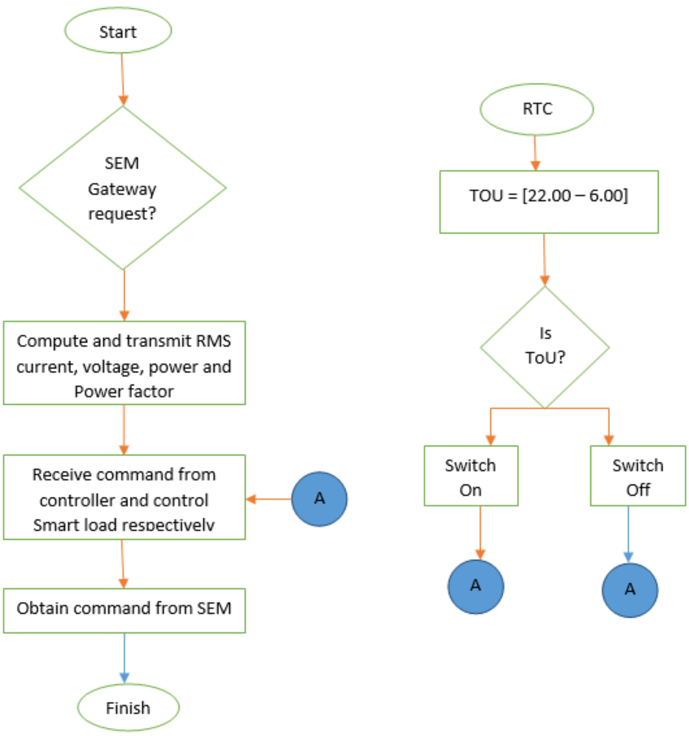

Figure 2 Flowchart for SSM

3.3 Cost optimization algorithm

The ToU tariff significantly influences consumers' energy costs. The development of a load scheduling algorithm has the aim of reducing energy costs. But not all appliances are vulnerable to this algorithm. Depending on whether a customer wants to permit schedulable operation, appliances in a house are classified as schedulable or non-schedulable. The load controller in every device that may be scheduled employs this method. As a result, the SEM algorithm operating in the SEM unit and the load scheduling algorithm operating in the load controller of a schedulable appliance both regulate all schedulable appliances.

The SEM unit transmits time information to any appliances that may be scheduled. The load controller of a scheduleable appliance determines the device's status depending on the

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time zone. An appliance's daily use requirement is established depending on the consumer's daily consumption. In order to provide the consumer an incentive of Indian rupees 1 per unit, the algorithm is configured to use the appliance as much as possible between 22:00 and 06:00, as illustrated in Fig. 2. The appliance must be shut off at times of high load in order to avoid fees, regardless of how long it needs to run. If the necessary time of operation exceeds eight hours, the appliance may operate from 10:00 to 18:00 during non-peak load hours, when neither an incentive nor a penalty is applied. If not, the appliance is turned off and set to run between 2:00 and 6:00, during which time a reward is provided. In the event that an appliance cannot be operated for the required amount of time on any given day because of dominance by the SEM decisive algorithm, that would happen if the electricity produced is inadequate the algorithm allows the appliance to operate for longer the following day. The daily demand is updated each day at 10:00 PM by adding the outstanding need from the previous day to the present day's requirement.

3.4 LoRa communication module

The suggested device made use of a relay module, sensors, an ESP32 microcontroller, and a RYLR896 LoRa module. The device was tested using the ESP32 microcontroller type Node MCU ESP32. With minimal electrical usage, the LoRa module, also known as the RYLR896 receiver, offers fervent long-range frequency for creating intercommunication and trustworthy disturbance security. This strengthened the robotic system. A printed circuit board had a microprocessor and an antenna built into it. (PCB). LoRa's integrated SimTech SX1276 motor and 127 dB dynamic range RSSI allow it to operate various products over distances of up to 12 km. The ESP32 microcontroller, a reliable and adaptable module with many built-in features, was used in the device. This gadget was put together using various electronic components.

It served as a gateway between various instruments and control buttons at the recipient end via cable connection, and between the user program and the LoRa module at the sending end via Wi-Fi connection. The system made use of a variety of instruments to keep track of the most recent state of the target setting or item. The ESP32 module's various I/O ports were used to link the instruments.

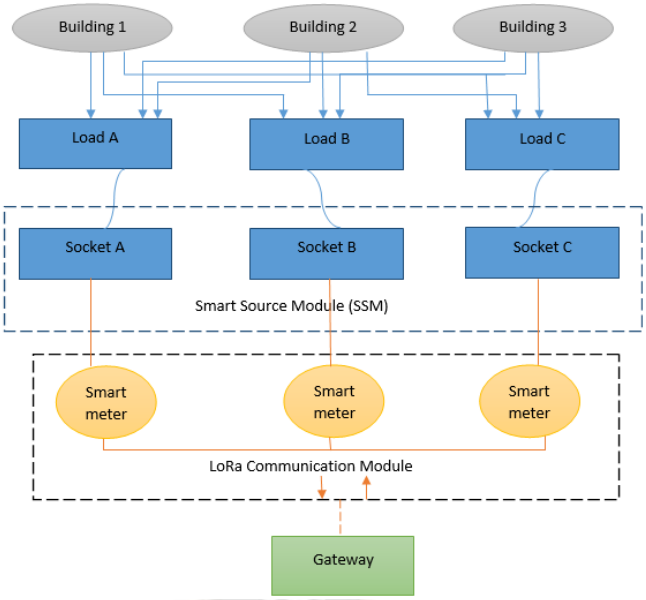

Figure 3. Architecture of SSM and LoRa Module

3.5 Data collection and processing

All user data from smart meters that have been gathered must be normalized by splitting them by the optimal value of the data, in this instance, the maximum load utilized (kW).

$$I_{(n,h-norm)} = \frac{I_{(n,h)}}{I_{(h-max)}} \quad (1)$$

Where: N is the overall amount of load profiles, and n represents the n-th load profile data collection, where h: denotes the h-th data point; h=1,..., H (H = total number of data points). $I_{(n,h-norm)}$: Data value normalized. Actual value of the data is $I_{(n,h)}$. The highest value of the data is $I_{(h-max)}$.

A brand-new method of data normalization called adaptive normalization was created specifically for non-stationary heteroscedastic time series. The entire data normalization process can be divided into three categories: (i) turning the non-stationary time series into a stationary sequence, which produces a set of separate sliding frames (ii) removing outliers; and (iii) actual data normalization. This procedure generates data that is provided to a learning technique as input. Take into account the adjusted series N= N1, N2, N3,... Nk and the time series T= T1, T2, T3,...... A new sequence R can be defined as follows given a sequence S of length n, its k-moving average S(k) of length $n - k + 1$, and a sliding window length,

$$R[i] = \frac{s\left[\frac{i}{\omega}\right](i-1)\mathrm{mod}\omega}{s^{k}\left[\frac{i}{\omega}\right]} \quad (2)$$

for all $1 \leq i \leq (n - \omega + 1) \times \omega$. There are $n - \omega + 1$ distinct movable windows in this series R. As can be seen, r_i,, all fractions have the same divisor, $s^{(k)}$ [i].

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This element is essential for preserving the time series' original pattern and guaranteeing that each number exhibits the same level of persistence. There are $\omega - 1$ input numbers and 1 output value in each section. Consider that in order to construct the series R, we must first compute s^k and then eliminate the k > ω – 1 first values of S if k > 1, or if the moving average order is greater than the number of inputs. For instance, the first component of the series S should be eliminated if k = ω= 3. First, we determine the degree of change for each exercise session.

$\alpha(s^k, r_i) = \frac{1}{\omega}\sum_{j+1}^{i+\omega-1}(s[j] - s^k[i])$ (3)

The lowest correction level that it can accomplish is chosen to be used in adaptive normalization. Our primary objective was to maintain the numbers of sequence R as near to 1 as possible, so we measured the difference between each fraction's numerators and denominators. A crucial stage in data preparation is outlier elimination from sample data, which is also crucial for time series analysis. The primary issue with data standardization is when anomalies appear at the time series' extreme limits, causing the minimum and/or maximum numbers to be illogical. Since values may be focused on a particular range of the standardized range, this has an impact on both the time series' overall numbers and the quality of the data standardization.

3.6 Prediction and scheduling model

The essential component of the entire energy system is prediction precision. The system merges and modifies the data based on the preset IoT within the function information package appropriate for deep learning models to learn when a bit of information is sent from each sending component to a central computer. To ascertain the power demand and associated factors of the energy demand on the power consumption end and transit pipeline system, the power forecasting system collects and employs these models. Regression analysis in that job is a frequent task. The system creates a layered perceptron by selecting the crucial components as input neurons and the expected data as output nodes. The BiGNN layer primarily computes the n-dimensional hidden state f_i of each time step, and then derives the hidden state matrix $F = \{f_{e-q}, f_{e+1}, \dots f_{e-1}\}$, where q is the duration of the sliding window, making short work of this task.

A row vector of the hidden state matrix E can be used to symbolize the values of each variable at each time point for the time series for building energy forecast. An associated column vector in that matrix can be used to describe the values of all factors at each time point. Afterward, the following temporal pattern characteristics are extracted:

$F_{i,j}^D = \sum_{k=1}^{q} F_{i(e-q-q+k)} \times D_{j,E-q+k}$ (4)

Formula (1) produces the time pattern matrix F^D corresponding to that variable by performing a convolution operation D with l filters and a kernel size of $1 \times E$ over the row vector of F. Let $F_{i,j}^D$ represent the outcome of the computation of the i-th row vector and the j-th kernel; F_i^D represent the i-th row of matrix F^D; Qx represent the trainable weight matrix; and F_e represent the hidden state produced by the recurrent unit layer. (RUL).

Next, the following criteria can be used to assess the varying temporal pattern:

$g(F_i^D, F_e) = (F_i^D)^E . Qx. F_e$ (5)

Following the encoder's receipt of the raw data, a_e, and F_{e-1}, F_e can be computed as follows.

$F_e = RUL_{encoder}(a_e, F_e)$ (6)

Let r_{e-1} be the hidden state from the previous time step, b_{e-1} be the previous output series, and r_e be the hidden state from the current time step.

The decoder can calculate $r_e = RUL_{decoder}(b_{e-1}, r_{e-1})$, based on b_{e-1} and r_{e-1}.Let the parameter matrix be Q_u. It is possible to connect the context vectors u_e and r_e to $r'_e = \tanh(Q_u[u_e; r_e])$. The parameter matrix should be Q_r.Then, using the SoftMax function, b_e can be solved:

$b_e = \mathrm{softmax}(Q, r'_e)$ (7)

Several variables have an impact on a building's energy usage. The following definition outlines the goal purpose of predicting building energy consumption:

$b' = G(A, B)$ (8)

Where $A = \{AC, FR, FA, LT, LG\}$ represents the numerous input factors, including an air conditioner, a refrigerator, a fan, a notebook, and a lamp.

$B = (k_e, k_{e-1}, k_{e-2}, \dots k_{e-n}\}$ represents the historical energy consumptions at the n prior times, where n is the frame duration of the historical data. $b^* = (b_{e+1}^*, b_{e+2}^*, \dots b_{e+m}^*)$ denotes the predicted values for the m future moments.

The learning rate of the parameter T can be constantly adjusted by the Adam algorithm, which makes parameter updates more stable. This method outperforms the majority of gradient-based algorithms in practical uses. In order to achieve a flexible learning rate, this study uses the Adam algorithm to repeatedly change the weight and bias of each prediction model node. Let n_e and m_e represent the prediction for the first-order moment of gradients, n'_e and m'_e represent the adjustment for the second-order moment of gradients, and γ represent the learning rate. Next, we have the following:

$n_e = \gamma * n_{e-1} + (1 - \gamma) * h_e$ (9)

$m_e = u * m_{e-1} + (1 - u) * h_e^2$ (10)

where n'_e and m'_e are considered to be objective approximations of predictions.

When the IoT devices and communication modules in a smart building are networked together, the cloud can receive

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the extracted knowledge from the data and use it to send alerts and notifications to the various smart devices in the building, including the IoT cooling and IoT heating systems, as well as the occupants themselves (via e-mail and SMS). We're assuming equal links here. The server component receives the estimated energy usage after the intelligence model's forecast of the heating and cooling loads.

The quantity of thermal energy needed for a space to maintain a comfortable climate for its occupants is known as the heating load (HL). A building's cooling load (CL) is the sum of the energy produced by the inhabitants, lighting, and machinery as well as the energy that is transmitted through the building's exterior (walls, floor, top, etc.). They are founded on the idea that the amount of energy needed for room chilling and heating is largely determined by the temperature differential between indoors and outdoors. Both need to be controlled based on a number of physical factors, including temperature, relative humidity, and air movement within the atmosphere, as they are both extremely susceptible to the construction and management of the structures. The HL and CL, which are also known as thermal burdens, are affected by a variety of physical variables, particularly the characteristics of how structures are constructed. This is because each building is viewed from the perspective of a heat network as a whole block.

They significantly influence the budgetary costs associated with the various seasons. Knowing how these variables will affect a building's heating and ventilation demands is crucial for forecasting. The effective functioning of air cooling, ventilation, and heating devices the following day depends on the ability to forecast the HL and CL of a structure. The goal of this research is to create a clever model that can forecast HL and CL under various input conditions, such as surface area, building height, and building direction.

IV. Performance analysis

The effectiveness of such an energy management program is evaluated using experiments that prioritize a device with different settings, simulate human satisfaction, and employ cost-saving techniques. The comparison of various existing models such as long short-term memory (LSTM) network and Recurrent Trend Predictive Neural Network based Forecast Embedded Scheduling (rTPNN-FES) based on RMSE, MSE, and MAE. These are compared wit LoRa_ bidirectional gated recurrent neural network (LoRa_ BiGNN) model

The MAE is a metric for comparing two continuous variables. The MAE used in this research is an average of the total differences between hourly real and hourly projected energy usage values derived from the AI models. Its composition is given as

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} y - y' \quad (11)$$

When y refers the hourly net energy consumption data, y' is the hourly predicted net energy consumption, and n is the sample size.

In the suggested model, evaluation is based on the MAPE's natural meaning in terms of relative error, which is a widely used metric for prediction issues. The MAPE computation is defined by the equation below. The difference between actual values and values projected by a prediction model is often measured by the RMSE. Its calculation is shown as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{y-y'}{y} \quad (12)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y-y')^2} \quad (13)$$

The efficacy of such an energy management software is assessed by studies that prioritize a device with various settings, model human happiness, and use cost-cutting strategies. Most air cooling and heating systems need to be repeatedly turned on and off since they are intended to function within a narrow temperature range or at a fixed temperature. As an example, the air conditioning device adjusts its temperature depending on the customer's surroundings. The ac motor starts and runs as soon as the interior temperature reaches the target level.

Furthermore, the equipment is exactly managed to the extent that it is continuously maintained inside the bounds of a user's comfy tastes. In this case, the Maximum Temperature in Degrees and data from the Moisture Temperature Controller are used to calculate the threshold number. At 7:43:25 p.m., the weather is below 22 °C on average. The microprocessor turned off the ventilation electricity as a consequence.

In this Table 1, 3, 5 shows the performance analysis of Cooling load and table 2,4,6 for heating load of RMSE, MAPE and MAE. Figure 4,6,8 shows the Performance analysis of heating load and figure 5, 7, 9 shows the analysis for cooling load. The performance is analysed by hours of the day and RMSE, MAPE and MAE metric.

Table-1 Comparison of methods for heating load - RMSE

Hours of the day	LSTM	rTPNN-FES	LoRa_ BiGNN
8:00 am to 12:00pm	2.17	1.53	0.21
12:00 pm to 4:00pm	2.23	1.52	0.18
4:00 pm to 8:00 pm	2.29	1.54	0.19
8:pm to 12:00 am	2.47	1.53	0.17
12:00 am to 4:00 am	2.34	1.54	0.18
4:00 am to 8:00 am	2.32	1.54	0.19

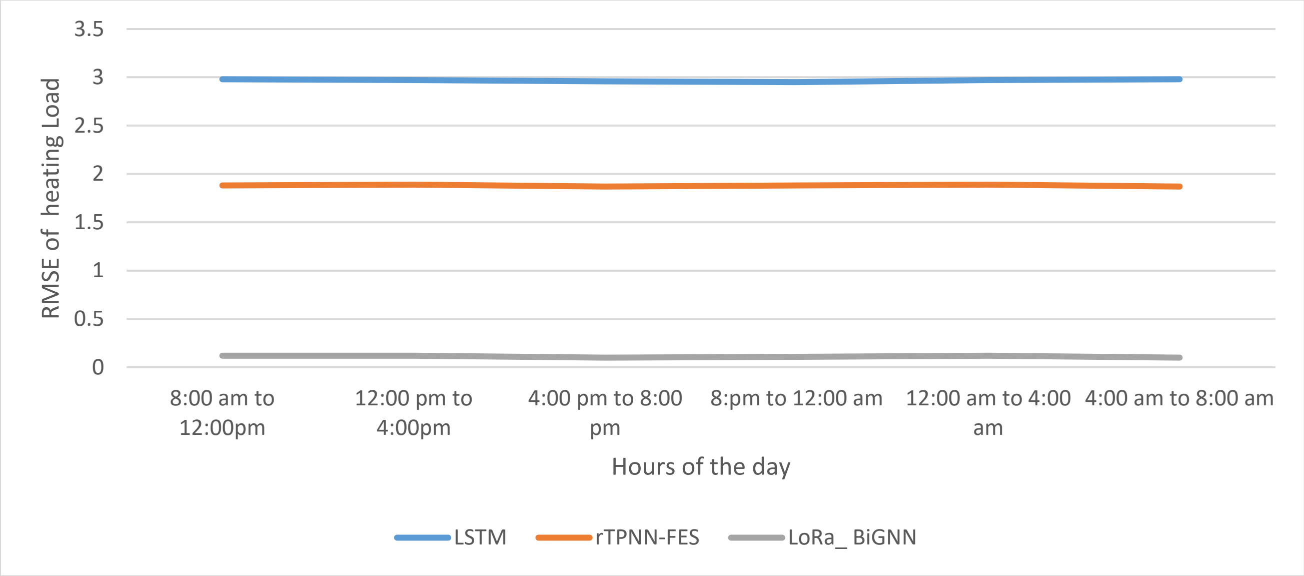

Figure-4 analysis of RMSE for heating load

Table-2 Comparison of methods for cooling load -RMSE

Hours of the day	LSTM	rTPNN-FES	LoRa_ BiGNN
8:00 am to 12:00pm	1.52	1.78	0.22
12:00 pm to 4:00pm	1.57	1.98	0.21
4:00 pm to 8:00 pm	1.53	1.9	0.08
8:pm to 12:00 am	1.55	1.87	0.19
12:00 am to 4:00 am	1.56	1.91	0.20
4:00 am to 8:00 am	1.58	1.87	0.21

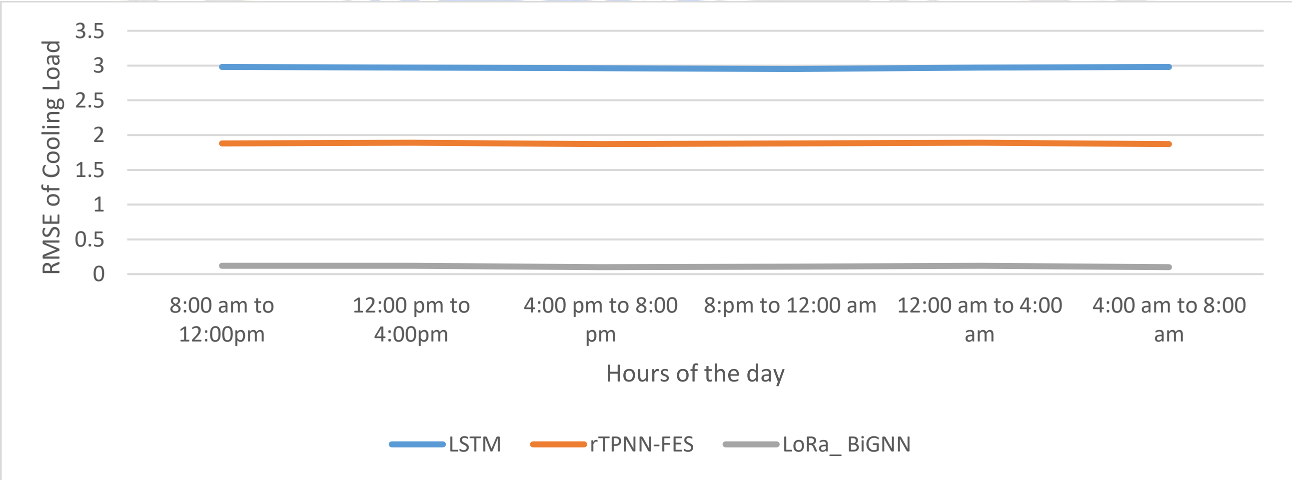

Figure-5 analysis of RMSE for cooling load

Table-3 Comparison of methods for heating load -MAPE

Hours of the day	LSTM	rTPNN-FES	LoRa_ BiGNN
8:00 am to 12:00pm	2.01	2.89	0.22
12:00 pm to 4:00pm	2.03	2.90	0.23
4:00 pm to 8:00 pm	2.03	2.93	0.24
8:pm to 12:00 am	2.02	2.92	0.25
12:00 am to 4:00 am	2	2.91	0.21
4:00 am to 8:00 am	2.01	2.97	0.24

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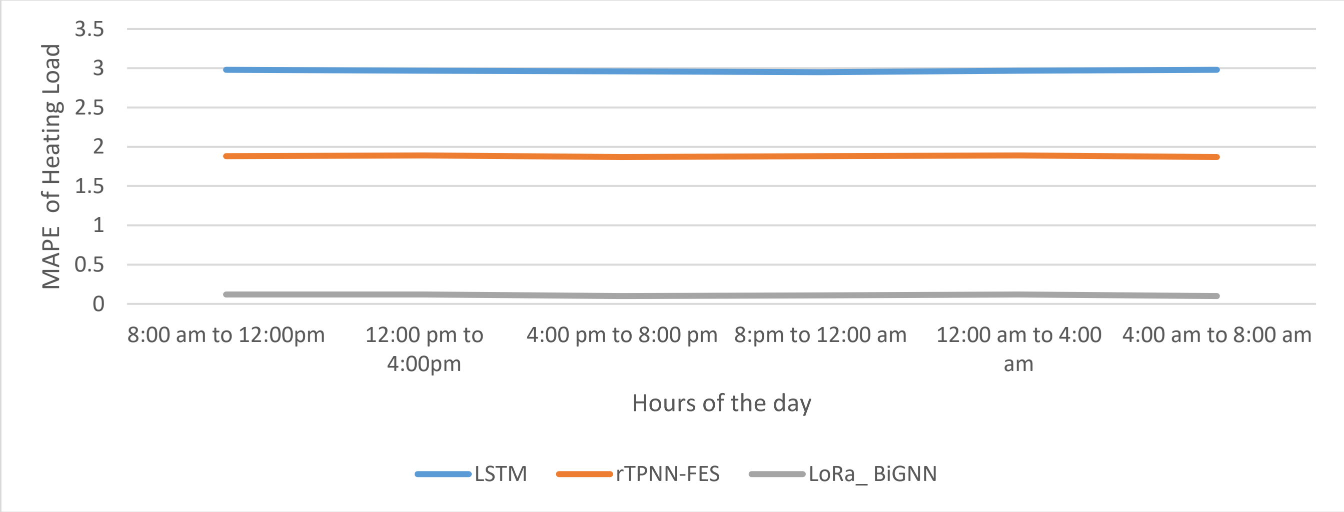

Figure-6 analysis of MAPE for heating load

Table-4 Comparison of methods for cooling load -MAPE

Hours of the day	LSTM	rTPNN-FES	LoRa_ BiGNN
8:00 am to 12:00pm	1.33	2.89	0.22
12:00 pm to 4:00pm	1.32	2.90	0.23
4:00 pm to 8:00 pm	1.35	2.93	0.24
8:pm to 12:00 am	1.34	2.92	0.25
12:00 am to 4:00 am	1.33	2.91	0.21
4:00 am to 8:00 am	1.35	2.97	0.24

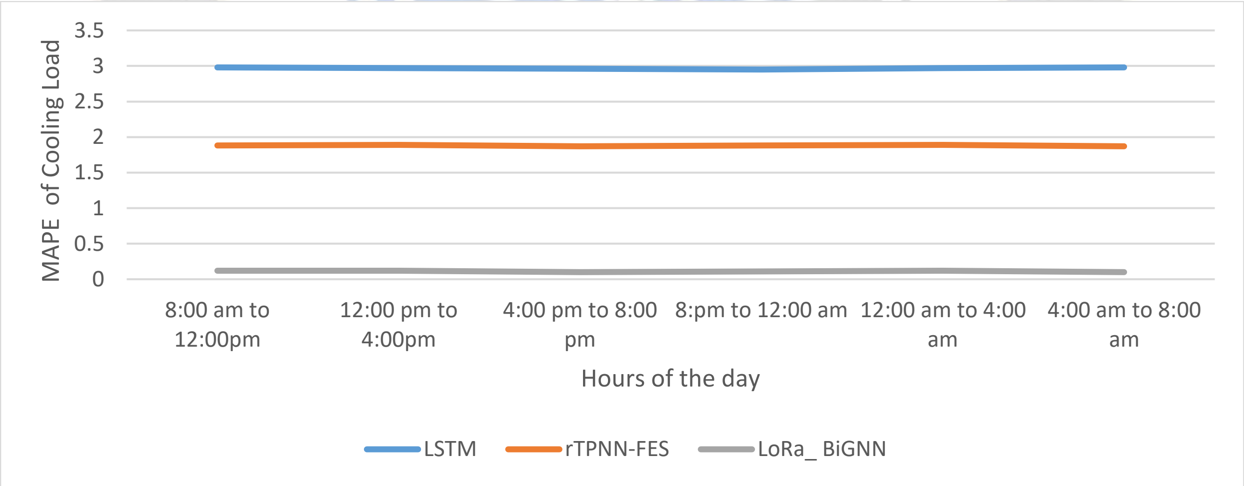

Figure-7 analysis of MAPE for cooling load

Table-5 Comparison of methods for heating load -MAE

Hours of the day	LSTM	rTPNN-FES	LoRa_ BiGNN
8:00 am to 12:00pm	1.31	1.88	0.11
12:00 pm to 4:00pm	1.32	1.87	0.12
4:00 pm to 8:00 pm	1.34	1.86	0.10
8:pm to 12:00 am	1.33	1.85	0.11
12:00 am to 4:00 am	1.33	1.84	0.12
4:00 am to 8:00 am	1.34	1.85	0.10

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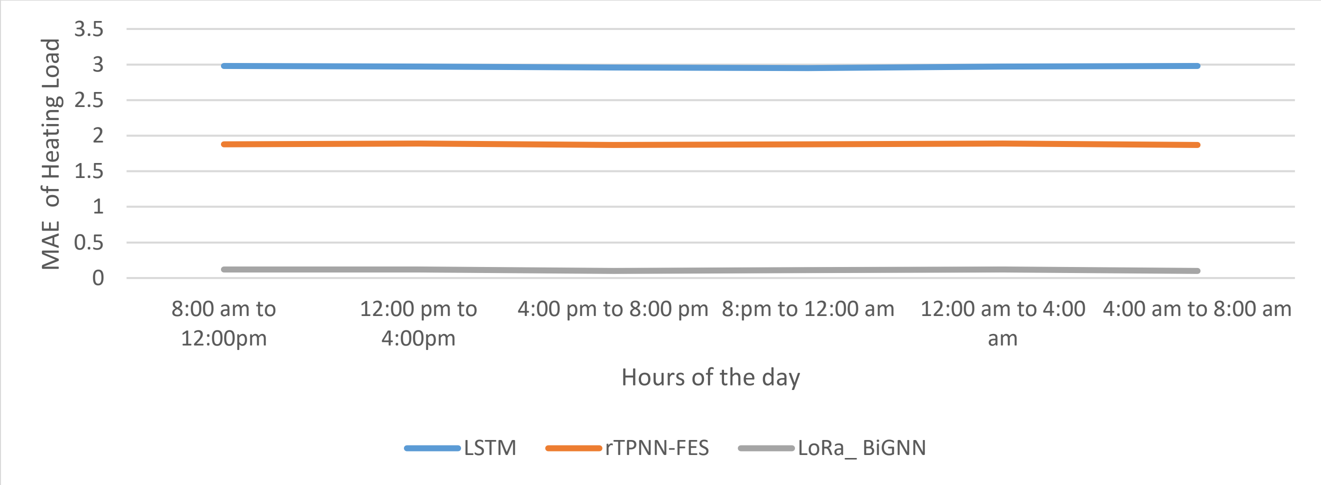

Figure-8 analysis of MAE for heating load

Table-6 Comparison of methods for cooling load -MAE

Hours of the day	LSTM	rTPNN-FES	LoRa_ BiGNN
8:00 am to 12:00pm	2.98	1.88	0.12
12:00 pm to 4:00pm	2.97	1.89	0.12
4:00 pm to 8:00 pm	2.96	1.87	0.10
8:pm to 12:00 am	2.95	1.88	0.11
12:00 am to 4:00 am	2.97	1.89	0.12
4:00 am to 8:00 am	2.98	1.87	0.10

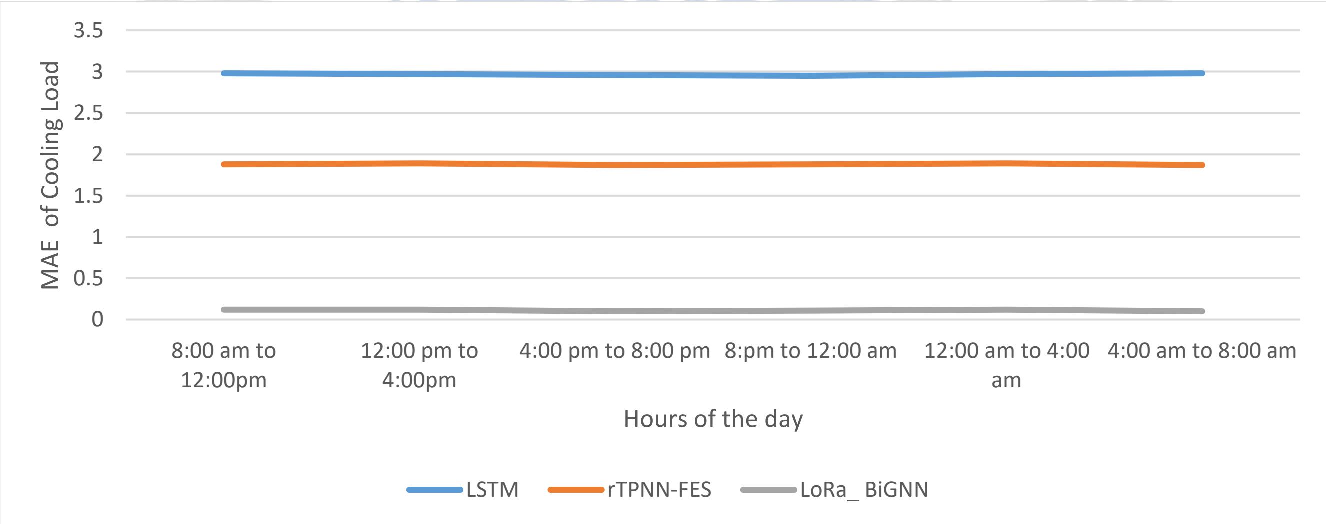

Figure-9 analysis of MAE for cooling load

Table 7 Comparison of overall performance with Existing method

	Heating load (kWh/m^2)			Cooling load(kWh/m^2)		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE
LSTM	1.34	1.57	2.03	2.98	2.4	1.35
rTPNN-FES	1.89	1.9	2.93	1.89	1.54	2.31S
LoRa_ BiGNN	0.11	0.21	0.24	0.11	0.18	0.23

From the above analysis, the existing method LSTM, rTPNN-FES is compared with the proposed method of LoRa_BiGNN for the metrics of MAE, RMSE and MAPE. This results reveals that all the metric error values are

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reduced to 0.11 of MAE, 0.21 of RMSE and MAPE of 0.24 for heating load (kWh/m2) and the 0.11 for MAE, 0.18 of RMSE and 0.23 of MAPE respectively. From this, the proposed method is very effective with LoRa communication module.

As was discussed in the sections that came before this one, there are two distinct types of home appliances, namely those that can be scheduled and those that cannot be scheduled. The suggested controller shifts the scheduleable loads to peak off hours in order to bring down the overall cost of power when the ToU tariff is in effect. In this instance, the controller makes use of data from the peak hours of the utility in addition to the information it receives from the RTC module. The controller delays the charging of the batteries (i.e., a schedulable load) until the peak-off hours, which in this scenario begin at 10 o'clock at night, in order to save money on the cost of the power.

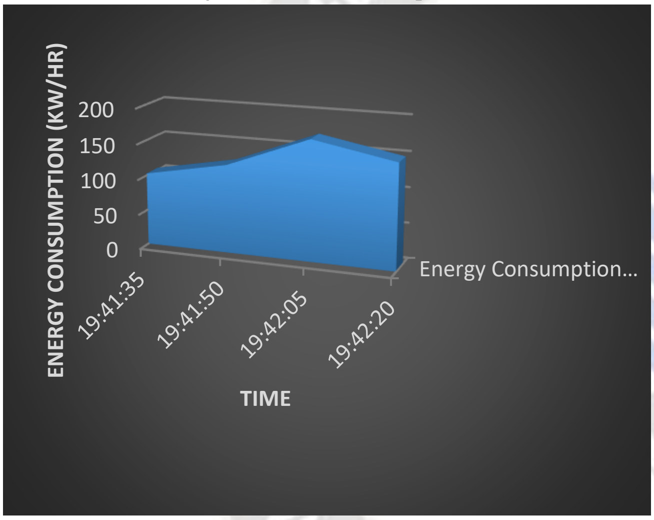

Figure 10. Graphical Representation of power consumption

The website was developed to provide electrical data in real-time, such as consumption of electricity. The login details are used to access the online portal only by those who have the required authorisation. The smart meter data repository is available to the user after a successful login. In this case, the user must first choose the desired laboratory and then input the appropriate day and time in order to see the present energy use of any laboratory listed on the website. The acquired electrical parameters are shown on the next page after choosing view, which takes you there. The total energy consumption for the selected laboratory will be shown at the bottom of the page. It is possible to check the power use trend graph from the main page, which is seen in Fig. 10. The user must fill out the login information on the login page. The user may access the home page after successfully logging in to the website. On the main page, the user may choose from a number of laboratories, look at power usage statistics, an energy consumption trend graph, and real-time data on energy use. Users and visitors may check it out to learn more about the project's objectives and details.

V. Conclusion

In this research, we looked at the management and control of distributed energy resources in scenarios related to smart buildings. Utilizing LPWAN solutions, the diverse communication infrastructure needs (such as indoor/outdoor covering of vast regions) are resolved. The use of LoRaWAN is specifically advocated in this article because it outperforms other technologies, as shown by the testing validation in terms of inaccuracy. The analysis showed that when a combination of straightforward sensors and sophisticated devices (with a monitoring time interval of 15 minutes and a supervisory control interval of 3 hours) is taken into account, the created data model, that focuses on LoRaWAN characteristics, has the capacity of managing and maintaining more than 10,000 smart nodes. To minimize the cost of power, it also takes into account the ToU tariff and uses the lower slab rate. Finally, a secure online portal connected to an IoT environment is established to provide access to the data on individual load power usage. The daily and monthly power usage of an appliance may be seen on a graphical user interface (GUI), and the database of an energy management system can be accessed for additional analysis. Future work focused on presenting an innovative system that uses security measures for preserving the building's associated equipment by taking benchmark temps into account. Additionally, mobile phone applications can be used to remotely watch and regulate energy usage inside structures in real-time.

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