ELECTRICITY LOAD AND PRICE FORECASTING USING AN INTELLIGENT HOME ENERGY MANAGEMENT SYSTEM

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1. RESEARCH PROBLEM

With the development of technology, many fields of the world have been changed and upgraded. Though Sri Lanka developed in some areas, the Whole electricity generation, distribution and consumption management systems still have not changed. These systems still follow manual techniques yet. For instance, due to supply and grid imbalances today, most Sri Lankans experience lengthy power outages. Because its worst economic crisis to find enough dollars to import fuel and some sudden breakdowns in primary coal power plants create a drop in power generating capacity. Currently, the government is struggling to give sustainable solutions to resolve this issue. To avoid the load demand exceeding the system's total capacity, the authorities are only considering planning power outages at peak hours in different areas. However, it might not be a long-lasting solution. Because the reasons are that now Sri Lankan population growth rate is much higher relative to past decades, massive construction and developments will happen in many cities very quickly. As a result, the capacity of our primary power plants cannot meet this demand.

For this reason, electricity dispatching is much more challenging than in the past, and new technologies and tools are required to ensure a real-time balance between demand and supply. Therefore, Authorities must think of a way to convert their traditional grid to a smart grid in extremely low-cost smart meters and use forecasting methods to save energy and be ready to face these energy issues in future. Otherwise, for the next 100 years, we will be badly experiencing daily power cuts.

To solve the above issue, as a country, we need to utilize the newest technologies and forecasting models to be ready to face future problems. Though there are previous works on electricity load and price forecasting, all the research papers state their final results based on old datasets without considering weather features. As a result, these proposed models do not meet the accuracy when used in the real world. On the other hand, Most of the Research topics on demand side management also have the same practical issue. As a base step in this study, an Intelligent Home Energy Management System was proposed to solve most practical difficulties in previous most researches done by others researches and increase machine learning load and price forecasting models' accuracy and performance.

2. STATE OF ART

Currently, there are very few researchers focused on weather features for forecasting. In the paper [1] Load forecasting model was proposed based on Long Short Memory (LSTM) recurrent neural network with weather features as input. According to paper [3], most previous research and their proposed Methodologies on load and price forecasting have different drawbacks. Some are high computational time, some proposed models are complex, unstable, and inaccurate, and some methodologies are not functioning for larger datasets. Therefore, maintaining better performance and higher accuracy in models is much needed in load and price forecasting. They proposed a mix of machine-learning and deep-learning-based Models to solve these issues. The hyperparameter optimization technique was used with the ensemble learner to achieve optimum precision and used feature engineering techniques in the model-building process to improve the performance of the Model.

The Paper [4] add a value flow in the smart grid using innovative services, market mechanism and information flow. They sketch a conceptual framework of the Cyber-Physical-Power-System

(CPPS) by interrogating with Power Internet of Things (PIoT). Using CPPS, they propose a robust smart grid with global information interaction, intelligent decision making, and real-time agile control. Finally, for illustration purposes, they conducted a case study regarding Home Energy Management Systems (HEMS)In paper [2], a solution for HEMS was proposed with direct current (DC) Power management. In their HEMS, smart DC sockets with load-shedding algorithms were used to control home devices with priority. The home devices were turned on or off by smart sockets only according to the energy consumption threshold at each sampling period.

Based on the above background, I have proposed an intelligent Home Energy Management System. The proposed HEMS makes the following contributions.

- Using both edge computing and cloud computing technologies and client-server architecture were prioritized in the HEMS design. The proposed HEMS architecture can be used with the current one-way grid system while maintaining our manual meter system
- Through our HEMS, every appliance is monitored individually in real-time and captures the data into a relational database running on the edge server.
- An CNN-RNN-LSTM Ensemble learner-based with grid search hyperparameter optimization regression model was proposed for precisely predicting future energy usage and cost in real time. Price and cost forecasting techniques help to reduce excessive energy generation and help to shift peak demand hours into different daytimes.
- A method to Use An auto-encoder to detect anomalies in energy usage patterns and find the starting and ending times of peak-demand hours according to individual usage.

- A database-driven method to flatten the demand curve of an individual consumer using forecasted results and a threshold value. It will be beneficial to both consumers and suppliers to save money

3. METHODOLOGY

In this research, the main algorithm consists of 2 main parts.

1. Load and price prediction for long-term and short-term purposes using an ensemble model.
2. Use LSTM auto-encoder for anomaly detection on the observed dataset.

3.1. Network design

In traditional HEMS, energy management and planning efficiency is very low due to insufficient energy consumption information collection and analysis. Nevertheless, With the development of network technologies, most power grids were widely integrated with PIoT and CPPS to make the HEMS more powerful and intelligent. This research proposed a modified HEMS consisting of four main layers, each focusing on different activities. Those are-

I. Physical layer – data collection
II. Network layer – data transmission
III. Edge layer- data management
IV. Cloud layer – value creation

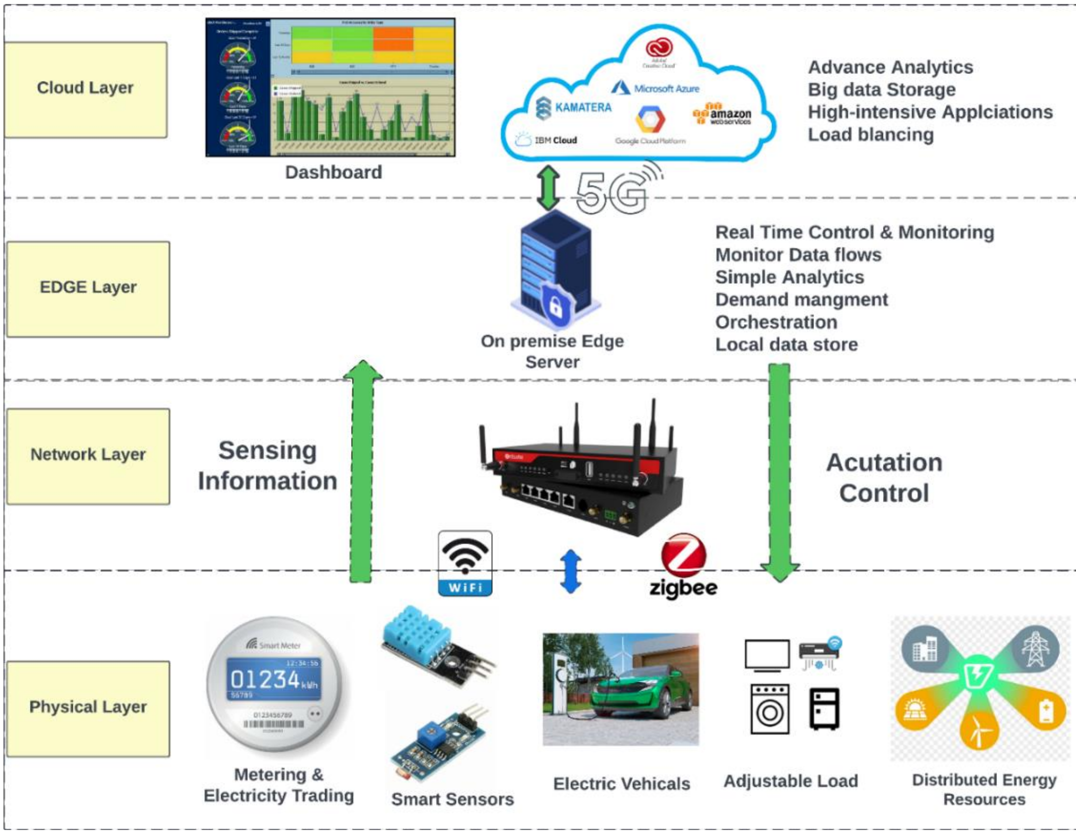

Figure 1- Architecture of an intelligent home energy management system

The physical layer consists of household electric appliances, sensors, data collection devices and electric actuators. The data collected from the physical layer are transmitted to the network layer using Wi-Fi or ZigBee communication technologies. The reason for selecting WI-FI and ZigBee was that WI-FI only could make a star topology. If the device loses the connection, there is no alternative path to make the connection and rebuild the WI-FI network. But ZigBee devices can build a mesh topology, and if the device loses one connection, it has several other connections to maintain the network without interruption.

Technology	Standards	Data rate[a]	Distance covered	Latency	Cost	Scope
ZigBee	IEEE 802.15.4	Low	100 m	50 ms	Low	HAN
WLAN	IEEE 802.11ax	Very high	70 m	3 ms	Medium	HAN and NAN
	IEEE 802.11ac	High	70 m	10 ms	Low	HAN and NAN
	IEEE 802.11n	Medium	50 m	15 ms	Low	HAN
	IEEE 802.11g	Medium	50 m	15 ms	Low	HAN
Cellular	2G	Low	35 km	300 ms	Low	HAN and NAN
	3G	High		100 ms	Low	HAN, NAN, and WAN
	4G	High		10 ms	Low	HAN, NAN, and WAN
	5G	Very high		<1 ms	Medium	HAN, NAN, and WAN
WiMAX	IEEE 802.16	Medium	30 km	50 ms	High	NAN and WAN
PLC	\	High	1–5 km	5 ms	Medium	HAN and NAN
Fiber-optic	\	Very high	>100 km	3 μs/km	High	NAN and WAN

[a]Data rate: low (<1 Mbps), medium (1–100 Mbps), high (100 Mbps-1 Gbps), and very high (>1 Gbps).

Table 1-Comparison of typical communication technologies for smart grid[4]

After that network layer forwards the environmental and energy consumption data to the edge layer. In the edge layer, all the data is stored in a database, which is used for load and price forecasting. According to the forecast results, several optimization algorithms will be executed and send the final control instructions to actuators from server to client to perform energy management for optimal energy consumption, cost, and user satisfaction. The edge layer is connected to the cloud layer. Using the cloud layer, the electricity service provider connected with the HEMS.

3.2. Hardware design

The following hardware items were proposed for use in the HEMS. For the actual implementation, we can use more accurate sensors and development boards depending on the budget. While designing the system, for actual implementation, WIFI modules were utilized. But for commercial development, ZigBee devices are more suitable than Wi-Fi devices. Following are some main devices and their specification used in the proposed HEMS.

I. PZEM-004T Sensor Module

The New PZEM-004T V3 module measures AC-voltage, AC-current, Power, Frequency and power factor. This module comes with three different current measurement options. Those are-

- 10A range with a built-in shut resistor
- 100A external closed Current Transformer
- 100A external split current transformer

Figure 2-Old PZEM -004T v1 100 A module + Closed Current Transformer

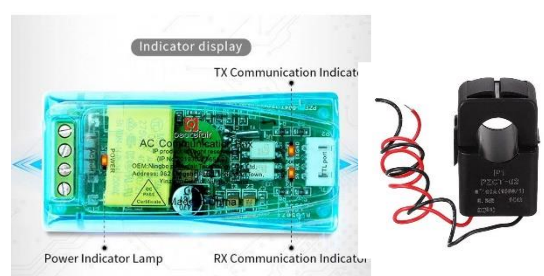

Figure 3- New PZEM -004T v3 100 A module + Split Current Transformer

The newest version of this sensor module has higher precision, faster refresh speed and more stability than older versions.

Table 2- Sensor Specification For 10 A PZEM-004T v3 module

Function	Measure Range	Starting Measure current /Power	Resolution	Measurement Accuracy
voltage	80~260V		0.1V	0.5%
current	0~10A	0.01A	0.001A	0.5%
Active power	0~2.3KW	0.4W	0.1W	0.5%
Power Factor	0.00 ~ 1.00		0.01	1%
Frequency	45Hz~60Hz		0.1HZ	0.5%
Active Energy	0~9999.99KWh		1Wh	0.5%
Communication Interface	RS485 interface			
Size	Length*Width*Height = (73.7) *(30) *(14.4) mm			
Power Supply	Need external 5v Powe supply			
Working temperature	-20ºC ~ +60ºC			

For the 100A module, only the change in the current measuring range is 0~100A, Active Power 0~23KW, current measurement starts in 0.02A, and all the other functions are the same as the 10A module.

II. NodeMCU development board and relay modules

This development board is used as the clients in the HEMS. All the relay modules and sensors are connected to this board. There might be multiple clients in the HEMS, and each client's objectives might differ. According to the command given by the server, this module acts at any time without delay. Usually, the ESP 8266 NodeMCU development board consists of a Tensilica Xtensa 32-bit LX106 RISC microprocessor, 128 KB RAM, and 4MB inbuilt flash memory.

Figure 5-ESP8266 NodeMCU development board

Figure 4- Single ,four and eight channel 5V relay module

III. Raspberry Pi Development Board

This development board was used as the central server in the HEMS. The proposed HEMS has a Raspberry pi Model 3B+ development board consisting of a 1.4Hz 64-bit quad-core ARMv8 CPU, 1GB RAM,802.11n wireless LAN with 0.1 Mbps LAN speed, 32GB SD card, and Raspbian Operating system.

Figure 6-Raspberry pi Model 3B+ development board

IV. DHT 11 Humidity and Temperature Sensor

Table 3-DHT11 Sensor specifications

Specification	Range
Operating Voltage	3.5V to 5.5V
Temperature Range	0ºC to 50ºC
Humidity Range	20% to 90%
Resolution	Temperature and humidity are both 16-bit
Accuracy	+-1ºC and +-1%

Figure 7- DHT11 temaparature and Humidity sensor

3.3. Categorization of Appliances

Domestic appliances are classified into three main categories. Those are-

1. **Non-Shiftable Appliances** - The appliances working time cannot be shiftable within the determined working period. (i.e., Refrigerators)
2. **Shiftable Non-Interruptible Appliances** - The appliances that can be shifted. (i.e., washing machine, dishwasher)
3. **Shiftable-Interruptible Appliances** -The appliances can be switched on and off anytime. (i.e., humidifier, air-conditioner and electrical charring systems)

According to the above categories, the home appliances can be grouped like below. Their average power rating values might differ by manufacturer, and duration hours will vary according to the consumer's life pattern.

Table 4- Power ratings of different appliances of a single user with operational time.[6]

Category	Appliances	Power Rating (Kwh)	Duration(hr.)
Non-Shiftable Appliances	Refrigerator	0.3	24
	Television	0.6	3
	Tube Light	0.1	8
	Fan	0.1	4
	Air Conditioner	1.5	6
	Laptop	0.1	2
	Oven	1.7	2
Shiftable Non-Interruptible Appliances	Washing Machine	3	6
	Electric Iron	1	3
	Water Heater	1.1	6
Shiftable-Interruptible Appliances	Vacuum Cleaner	1.2	2
	Dishwasher	2.5	4
	Clothes dryer	3	5

Though every appliance has a labelled power rating value on top of the equipment. But while working, those rated power values might differ due to voltage and current variations. Therefore, through the proposed HEMS, individual appliance actual power values get from the sensor and keep it in a separate table in the Database. Those values are much-needed to run power consumption scheduling algorithms in peak load times.

3.4. Autoencoders for Anomaly detection

An Autoencoder (AE) is composed of two different networks in a series. The encoder part compresses the input into a lower dimensional space, and the decoder part attempts to reconstruct the input from the encoded representation [5]. In the beginning, the AE trained with the optimal inputs. At this time, AE will be tuned its parameters to reconstruct the input from the encoded representation. Then when we fed some time series data that had anomalies, the AE failed to reconstruct the input as it is. There might be high values in the loss function and some error matrices like Mean Square Error (MSE) and Mean Absolute Error (MAE). Each sample fed into the AE is classified as ‘Normal’ or ‘Anomaly’ based on the values obtained for the loss function. That means we can calculate the loss function's average value without anomalies. When there is an anomaly, the loss function value will be greater than the previous value.

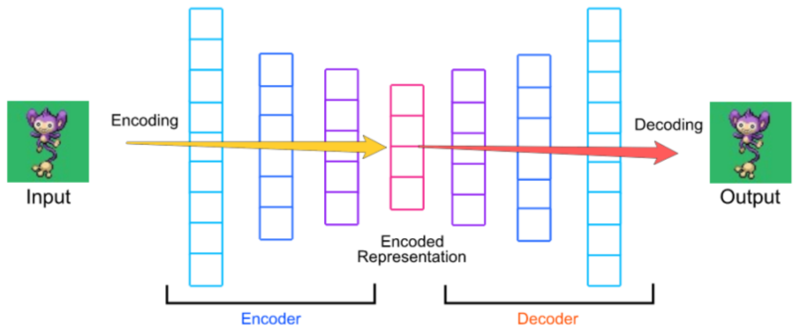

Figure 8-Internal structure of an Autoencoder

4. PROPOSED DESIGN

There are different types of energy management systems proposed by different researchers. They are-

- Community Energy Management Systems (CEMS)
- Factory Energy Management Systems (FEMS)
- Building Energy Management Systems (BEMS)
- Home Energy Management Systems (HEMS)

This research entirely focused on HEMS and its functions. However, these designs can be used in any place or building according to the situation. HEMS optimizes home appliances' energy usage and helps consumers incorporate other Demand Side Management activities. To build an Intelligent HEMS, all the devices have measured individual consumption, and we must maintain the client-server architecture. In the proposed HEMS, the server (Raspberry pi) can send commands to their clients (Node MCUs) and control the devices connected to each node Microcontroller Unit using a relay module.

Most countries, including Sri Lanka, still Use the Old energy meter for measuring electricity. On the other hand, as shown in Figure 2, the house wiring techniques are also identical. But in the current economic crisis, removing and replacing the old meter with a smart energy meter is not a sustainable solution. Therefore, while keeping the old meter, the individual equipment was measured using the sensors with the help of modified intelligent HEMS, as shown in Figure 3. Currently, The Pzem sensors are fitted inside the distribution board, and one bedroom monitors its inside temperature and controls its devices.

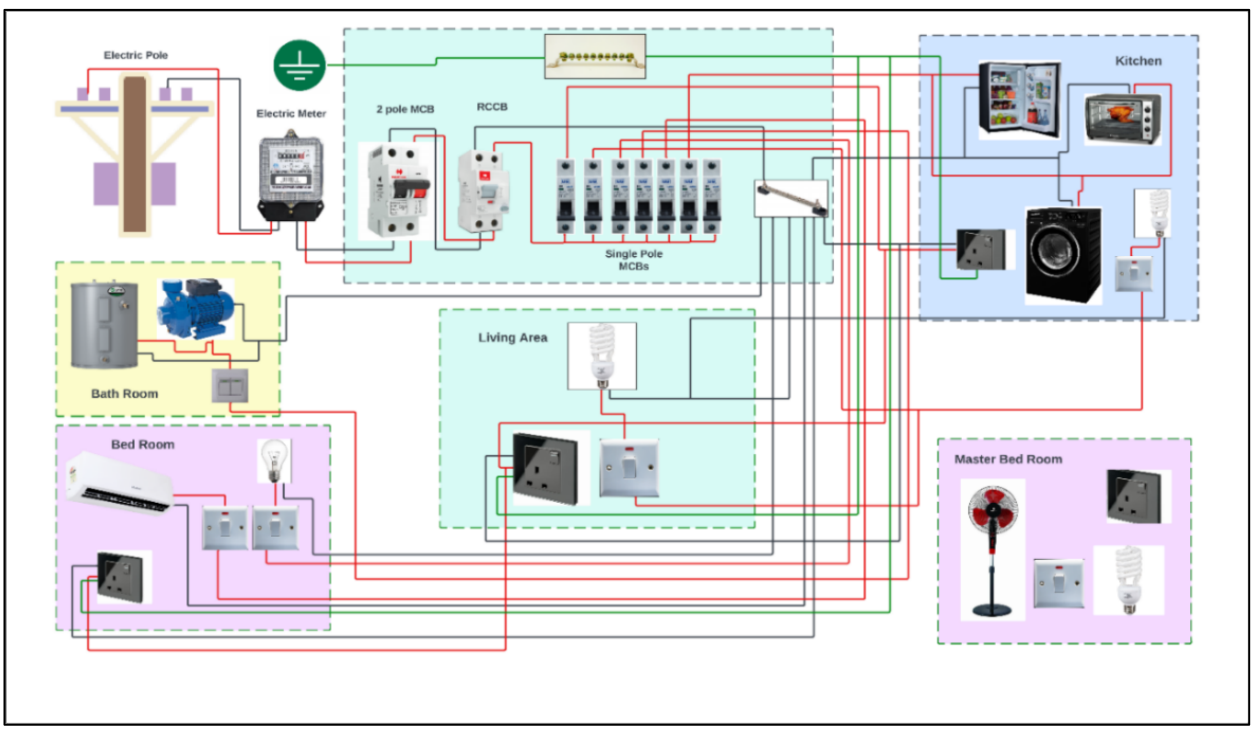

Figure 9-Traditional single phase house wiring diagram with old energy meter

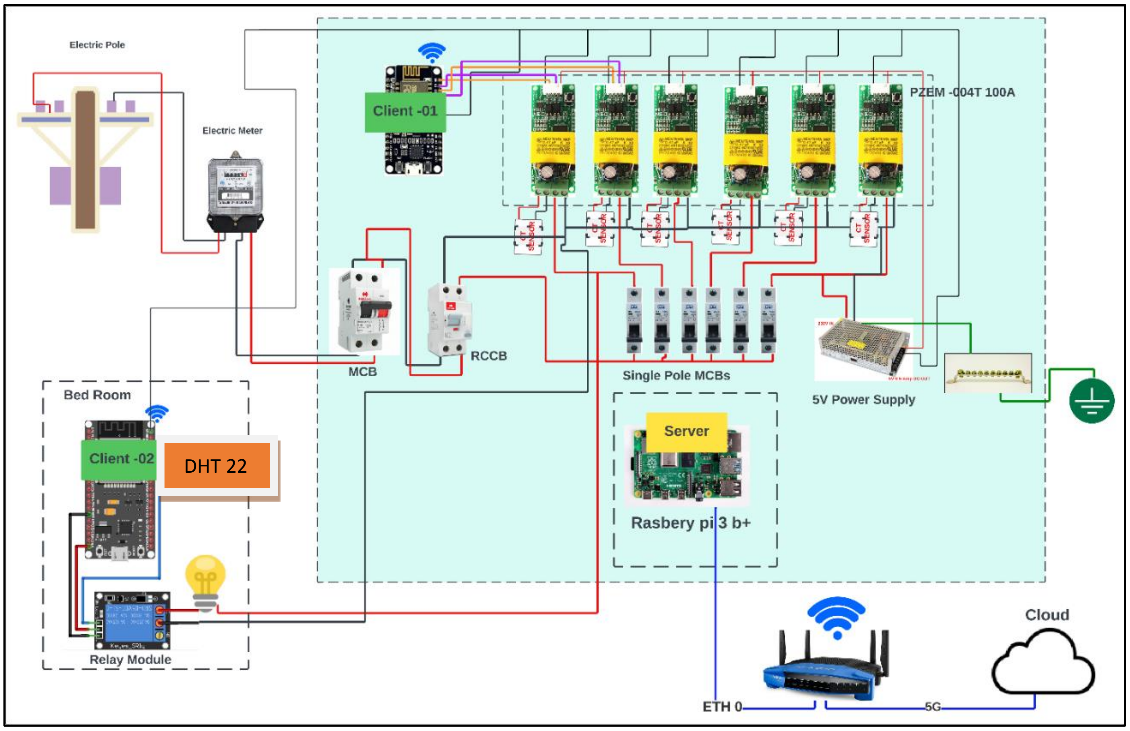

Figure 10-Proposed design for placing hardware items and sensors in HEMS

In the above design, data will be observed using external sensors and stored in a relational database inside the raspberry pi server.

- **Home Energy-Related data**

1. Date: Date in format dd/mm/yyyy
2. Time: time in format hh:mm:ss
3. Total_Active_Power: active household power (KW)
4. Total_Reactive_Power: reactive household power (KW)
5. Total_Voltage: minute average voltage(V)
6. Submetering_K_01 -It corresponds to the energy usage-related parameter of the Oven in the kitchen (i.e., voltage, power, energy, Power factor, current)
7. Submeetring_R1_01- It corresponds to the energy usage-related parameter of the Oven in the kitchen (i.e., voltage, power, energy, Power factor, current)

8. Unit Prices: The relevant unit prices for that period. The service provider will provide these data, and the price rates of a particular unit range will change from time to time.
9. Total price: total price for a relevant timestamp

❖ **Home weather-related and environmental data**

1. Date: Date in format dd/mm/yyyy
2. Time: time in format hh:mm:ss
3. City_temp: Outside temperature of the house
4. City_Hum: Outside humidity of the house
5. Temp_kitchen: temperature inside kitchen
6. Hum_kitchen: humidity inside the kitchen
7. Temp_Room1: Room1inside temperature and Hum_Room1: Humidity inside the room

Equipment's electricity functions and surrounding temperature values are gathered using sensors for all rooms and places inside the home.

4.1. Proposed Communication Architecture

While selecting the protocols for the HEMS following facts have been considered.

- ✓ In the design, both Server and Client nodes have their limitations in terms of resources, processing, memory capacity, and communication bandwidth. The HEMS Server and clients should be run for 365 days without interruption. Because if a power failer occurs, all processes running inside the server will be terminated, and restarting all services will take a considerable amount of time. Therefore, when the electricity is back, these devices will take some time to connect with the router and do the electricity usage measurements. So, avoid this, we need a battery backup system that can hold the device and its last state when it is active until the grid power is restored.
- ✓ In the Commercialized version, protocols used in the HEMS should require security along with cryptosystems.

The proposed HEMS uses the Message Queuing Telemetry Transport (MQTT) protocol for data communication between clients and server. Because MQTT uses less power to maintain connection and receive the message and send them, low power consumption quality will help increase the battery's lifetime in such a failure. On the other hand, MQTT supports simple security mechanisms and data synchronization with the cloud.[10] Flowing are essential methods and devices, and their functions labeled in Figure 10.

Subscriber- These are clients who are interested in getting specific info

Publisher - Publishers are all types of sensors placed in several different places and mainly on the distribution board in the HEMS.

Gateway -The device that connects different MQTT protocols together to communicate with each other.

MQTT Broker – This guarantees that subscriber get desired information from the publisher and handle publish data subscriber

Server- This stores the data in the Database, and that data will be used for load and price forecasting.

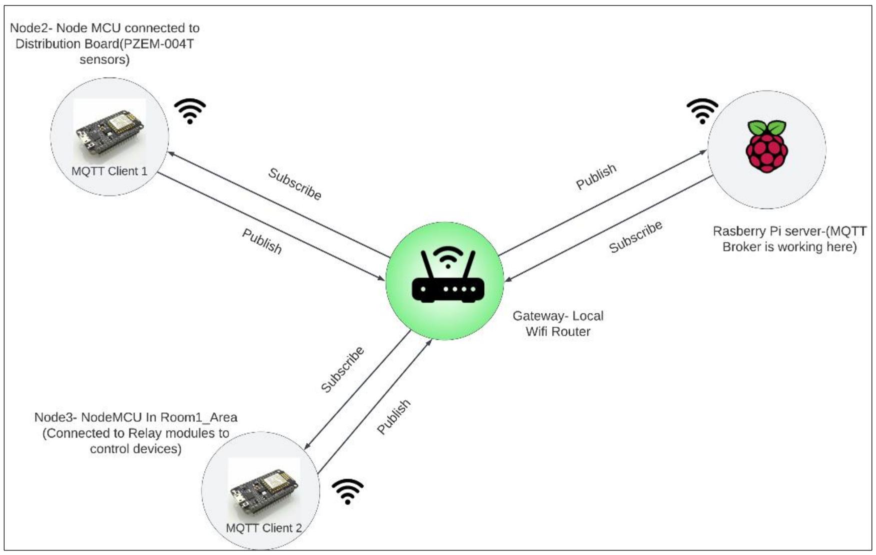

Figure 11-Communitation Articture of Proposed HEMS

4.2. Proposed Entity Relationship diagram designed for Database

The data obtained from the sensors are kept in relevant tables in the Database. Since the Database is running inside the raspberry pi module, we need to reduce the database size. Therefore, all the variable sizes are optimally named in the ER diagram. As Figure 10, we should maintain the structure. I assumed that there are majorly four areas inside the above Figure 8 wiring diagram drawn house. All the devices in each area are independently monitored and controlled by sensors and actuators.

On the other hand, the service provider must also convert their traditional grid system to an intelligent grid system. Hence, to reduce individual consumption, the service provider should automatically insert the full active demand details and forecast details for each Feeder and Grid substation that affects the particular house clusters.

Table 5 Part of feeder and grid substation assigned table inside Sri Lanka(www.cebcare.ceb.lk)

Grid Substation	Feeder	Affecting Area
Horana	Feeder 03	Munagama, Hoarana Town , PadukkaRoad,Millawa etc.
Kurunegala	Feeder05	wariayapola
Balangoda	Feeder03	Madampe, kawuduwawa,alpitiya etc.
Thulhiriya	Feeder05	Giriulla

As per the above table, every house in Sri Lanka belongs to one grid substation and feeder. Therefore, those feeder lines should continuously monitor for the current and voltage using suitable sensors. Those service provider data help to decide which houses and their devices should be controlled in peak demand hours, and which power plants should be worked during peak demand hours to save customer and service provider costs. The following Figure 10 shows the ER diagram drawn for the Proposed HEMS.

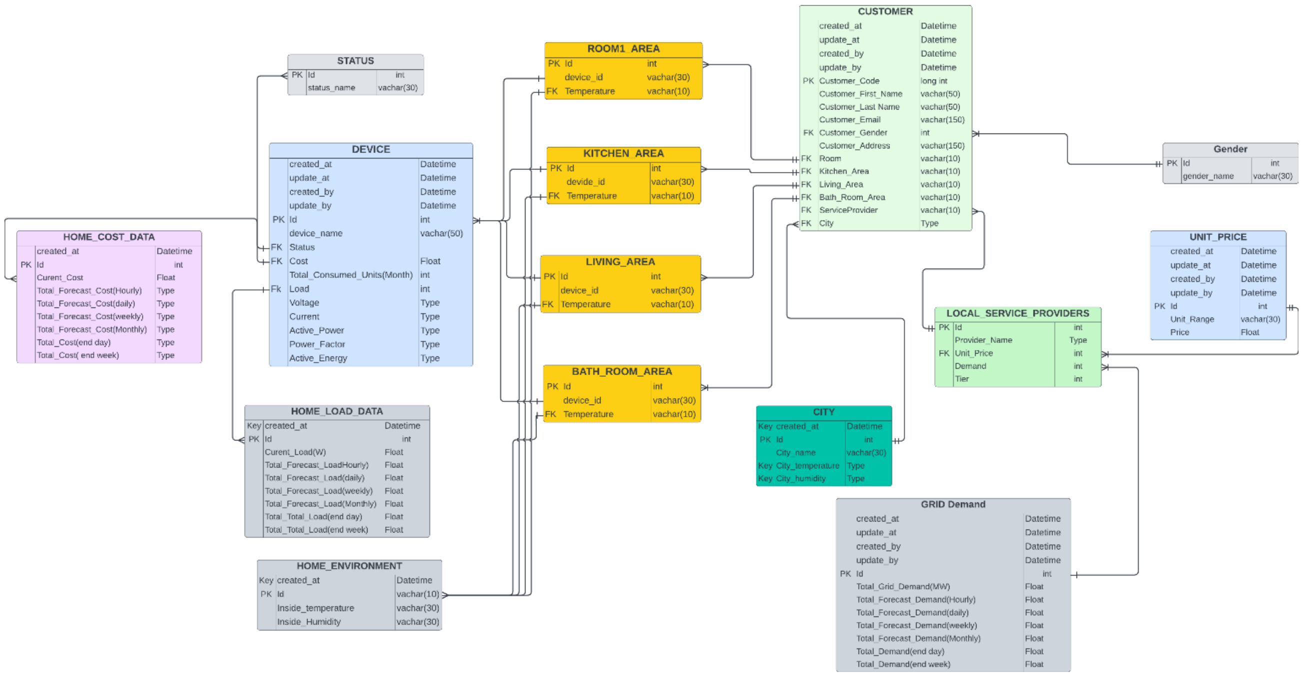

Figure 12-Proposed ER Diagram for the Database

4.3. Proposed Model for predicting Electricity Load and Price

To predict the energy load and price forecasting, the following step was Proposed.

1. Load data (The HEMS server's Database)
2. Feature selection Using RF and XG-Boost.
3. Feature Extraction Using RFE
4. Splitting of data into training and testing.
5. Load the RNN, LSTM, and CNN layers and parameters.
6. Tunning the RNN, LSTM, and CNN parameters using the Grid search optimization algorithm
7. Predict Price and load daily, weekly and monthly
8. Performance evaluation

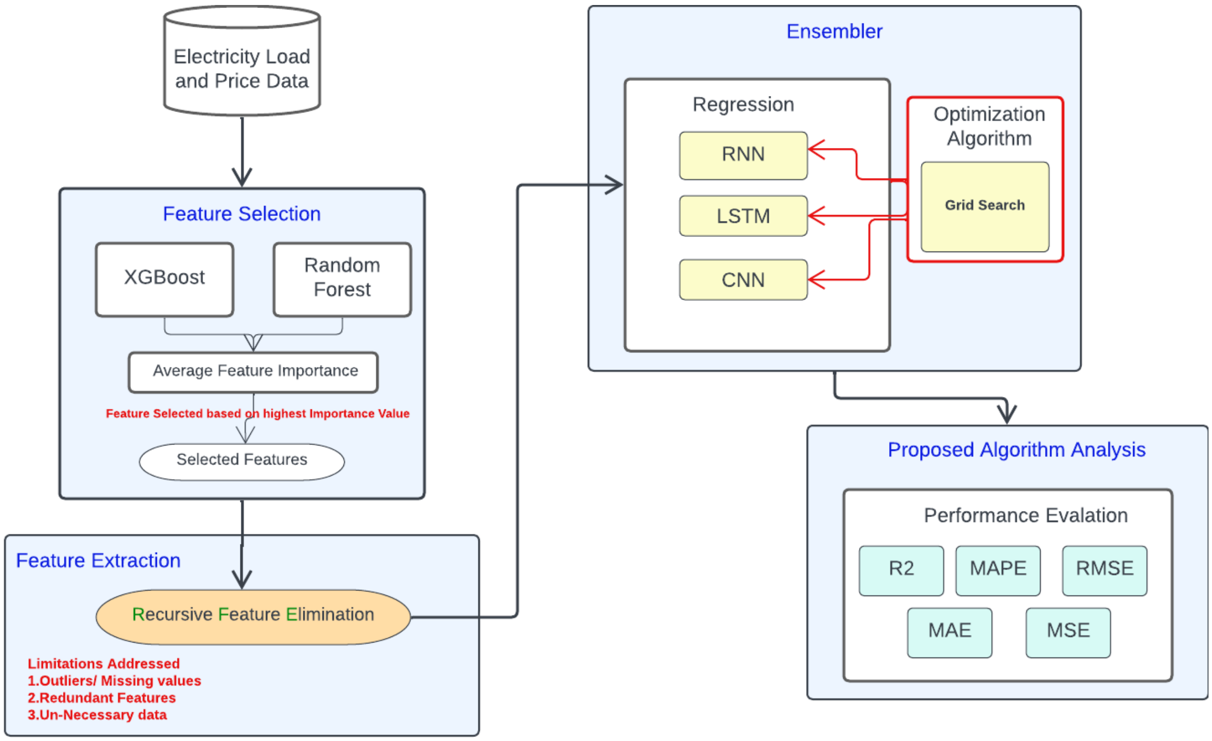

Figure 13-Proposed Model for Electricity Load and Price forecasting

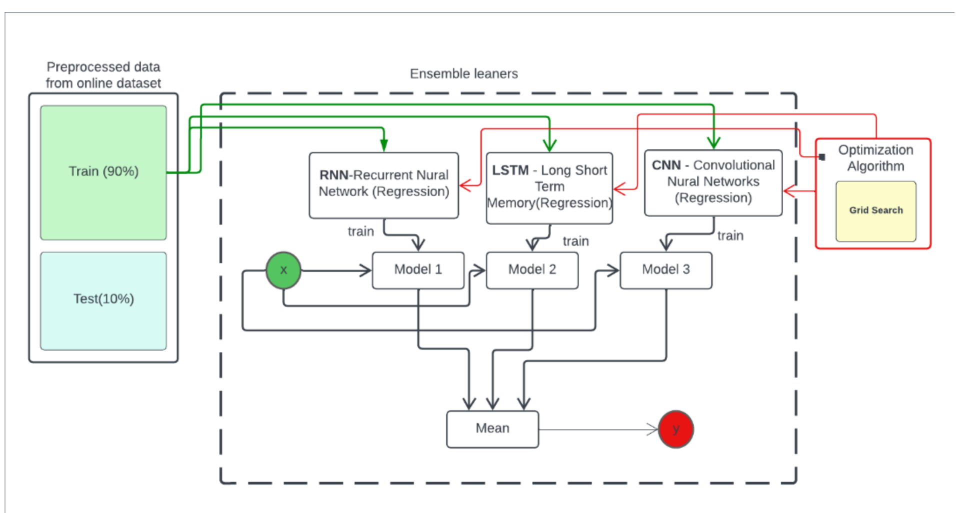

Figure 14-Overview of the ensemble learner

- **Load data**

To train the model HEMS database should contain at least data points for up to two years. Then 90% of the data will be used as training data, and the remaining data will be used as testing data.

- **Feature selection**

Selecting more critical features from the Database or dataset is known as feature selection. Depending on the feature importance values calculated from RF and XG-Boost algorithms help to find features that highly impact the target feature. Removing the features that are not needed improves the simulation time and reduces the computational complexity.

- **Feature Extraction**

Recursive Feature Elimination (RFE) is a tool for obtaining a set of attributes from a dataset. It removes the weakest feature recursively till the specified number of features is reached. The Random Forest algorithm was used for the recursive feature elimination process. On the other hand, manually deciding the final number of features is not good at all. Therefore cross-validation is used with RFE to solve this problem. Using RFECV (Recursive Feature with Cross Validation) algorithm, it self-selects the optimal number of features. The final aim of using RFE was to remove the redundant features and select the optimum and most relevant feature.

- **Grid Search**

The main aim of using Grid search is to obtain optimal values of the model hyperparameters. These parameters usually control the Model's accuracy and performance. Therefore, grid search uses different combination of all the specified values for the model’s hyperparameters and calculate the performance of each combination and select the best value for the hyperparameters.

❖ Recurrent Neural Network

The standard Recurrent Neural Network (RNN) only uses a tanh activation function to activate the input and then directly passes it to the next layer without filtering the information flow and leading to the problem of long-term dependencies. As a drawback, such problems like vanishing gradient and long-term dependencies of this Model limited its capabilities in long sequence prediction tasks.

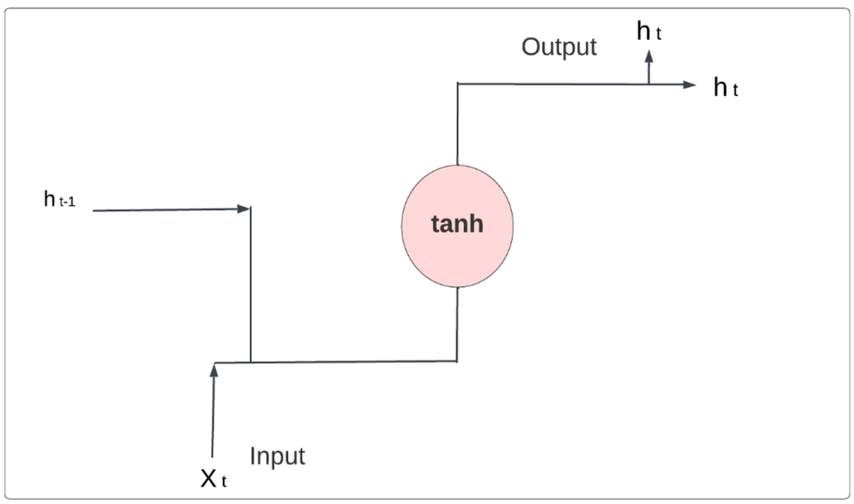

Figure 15-Internal Cell Structure of RNN

❖ Convolutional Neural Networks

Convolutional Neural Networks (CNN) provide better accuracy in non-linear problems such as electricity price and load forecasting. CNN belongs to the supervised deep learning algorithm. Firstly, a sequential model is implemented. Then it uses weight sharing concept to input data (X1, X2, X3, X4, X5, X6) to a feature map (C1, C2, C3, C4). Next pooling layer is applied to the feature maps of the convolution layer. According to Figure 15, the feature map's dimension is reduced to 2 after applying the pooling layer.

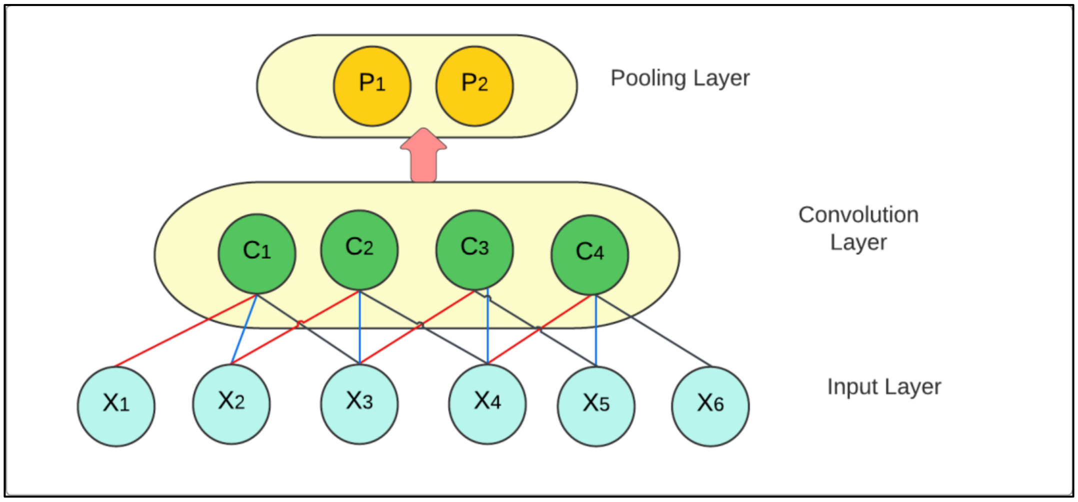

Figure 16-One dimensional Convolution and PoolingLayer

❖ Long Short-Term Memory

The next popular solution used for forecasting problems is the Long Short-Term Memory Network (LSTM). This is a recurrent neural network that works on time series data problems. The internal structure of LSTM consists of four main units. Those are the Input gate, Output gate, Forget gate, and cell status. The difference between the RNN and the LSTM is that RNN only has the function of temporary memory storage, and LSTM has the long-short term memory. Therefore, this internal memory and gates help to overcome gradient problems that occur in traditional RNN.

The computation process of LSTM can be shown below [11]:

$$f_{t} = \sigma(\omega_f[h_{t-1}, X_t] + b_f)$$

$$i_{t} = \sigma(\omega_i[h_{t-1}, X_t] + b_i)$$

$$o_{t} = \sigma(\omega_o[h_{t-1}, X_t] + b_o)$$

$$a_{t} = tanh(\omega_a[h_{t-1}, X_t] + b_a$$

$$c_{t} = f_t * c_{t-1} + i_t * a_t$$

Here f_t , i_t , o_t are the output values of the Forget gate, Input gate, and Output gate respectively. c_t refers to the memory cell and a_t refers to the update and the activation of the current cell status. X_t is the input vector and the h_t is the output vector result at time t. The ω_f , ω_i , ω_o, ω_a are the weight matrices and the b_f , b_i , b_o , b_a *are* the bias vectors. The σ is the Sigmoid activation function, and it can define as below:

$$\sigma(x) = (1 + e^{-x})^{-1}$$

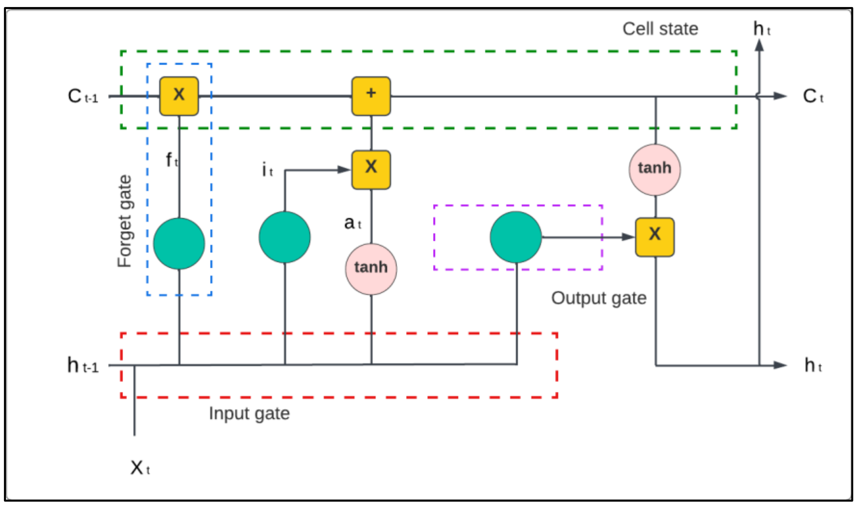

Figure 17-Internal cell structure of LSTM

4.4. Performance Evaluation

❖ To calculate MAPE, use the following formula:

Equation 1- Formula for Mean Absolute Percentage Error

$$\mathrm{MAPE} = \frac{1}{y} \sum_{t=1}^{y} 100 \left| \frac{S_b - S_a}{S_b} \right| \text{-----------------------------(1)}$$

Here S_b- Actual value, S_a- Forecast value and y –Total number of observations

- RMSE is the error rate by the square root of MSE. To calculate RMSE, use the following formula:

Equation 2- Formula for Root Mean Squared Error

$$\text{RMSE} = \sqrt{\frac{1}{\text{y}}\sum_{\text{t}=1}^{\text{Y}}(\text{S}_\text{b} - \text{S}_\text{a})^2} \text{ --------------------------(2)}$$

- MAE represent the difference between the actual and predicted values extracted by averaging the absolute difference over the dataset. MSE represents the difference between actual and predicted values extracted by squaring the average difference over the dataset. To calculate MAE and MSE, use the following formula:

Equation 3- Formula for Mean Squared Error

$$\text{MSE} = \frac{1}{\text{Y}}\sum_{\text{t}=1}^{\text{Y}}(\text{S}_\text{b} - \text{S}_\text{a})^2 \text{ --------------------------(3)}$$

Equation 4 - Formula for Mean Absolute Error

$$MAE = \frac{\sum_{t=1}^{Y}|(S_b - S_a)|}{Y} \text{ --------------------------(4)}$$

- R-squared represents the coefficient of how well the values fit compared to the original values. The value from 0 to 1interpreted as percentages. The higher value, the better the Model is.

$$\boldsymbol{R^2} = \mathbf{1} - \frac{\Sigma(\text{S}_\text{b} - \text{S}_\text{a})^2}{\Sigma(\text{S}_\text{b} - Z)^2} \text{--------------------------(5)}$$

Here the Z -mean value of the Actual values

5. OBTAINED RESULTS

An online data set was used to obtain the load and price forecasting results and plot the forecasted loads for one day, week, and month. The Online data set was PJM Hourly Energy Consumption Dataset, and it is over ten years of hourly energy consumption data in megawatts of some parts of the United States. Figure 11,12,13 all the forecasted points were plotted against the dates. The curve plotting was limited to the LSTM algorithm due to time constraints. For RNN and CNN, only the models were built and obtained accuracy value at last.

The forecasting simulation was done for the LSTM algorithm on the following specifictions:16GB RAM, a 4.8 GHz core i7 processor used, and the IDE environment visual studio code and the python language were used.

Dataset Link- https://www.kaggle.com/datasets/robikscube/hourly-energy-consumption

Codes (LSTM Prediction Model)- https://github.com/dhanushka365/SLEnergyConsumptionPrediction

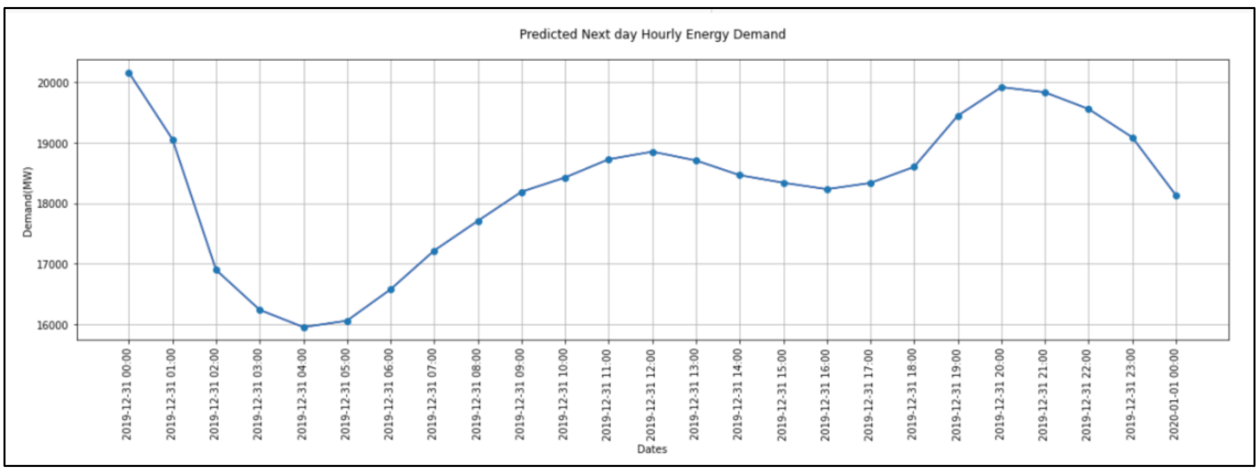

Figure 18-One Day load forecasting

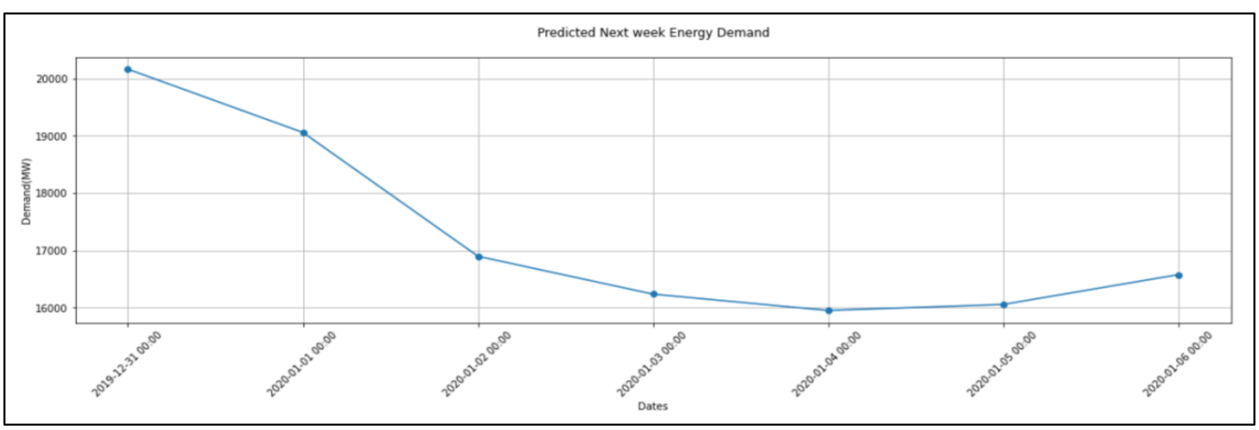

Figure 19-One week Load Forecasting

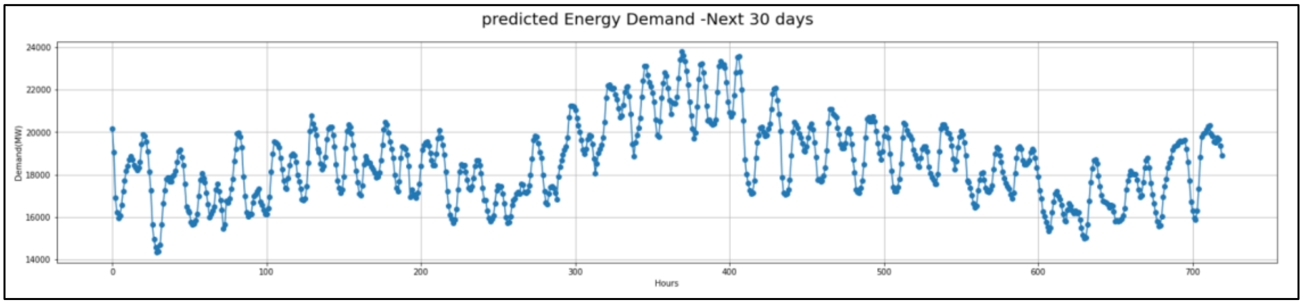

Figure 20-One Month load forecasting

For CNN and RNN above steps are yet to be followed to obtain similar results. After that, to optimize the above LSTM model grid search and for the final model ensemble, learner parts are also yet to be completed.

For the same dataset, an LSTM Autoencoder model was coded, and the below result was obtained. Here the python Ploty library was initiated to plot the output; hence it shows the value of every point in the curve.

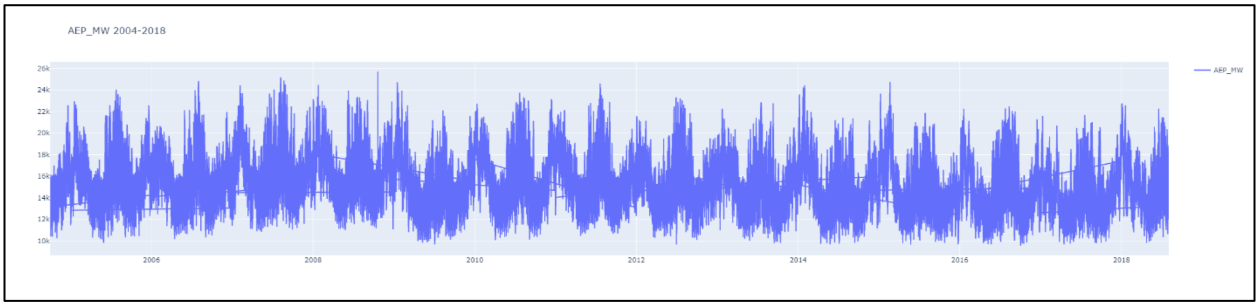

Figure 22 - The Load variation for toatal dataset

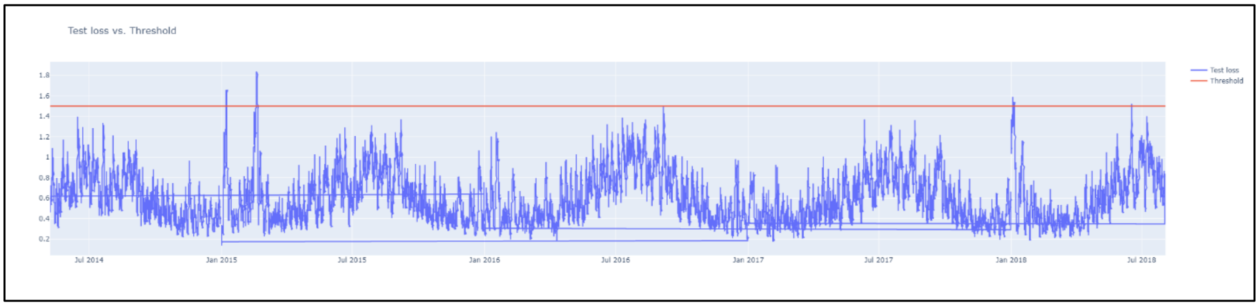

Figure 21-threshhold values is calculated and plotted as horizontal line

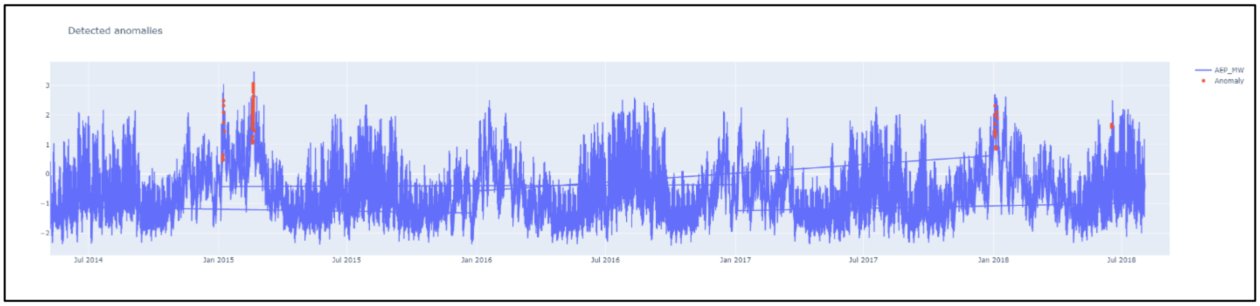

Figure 23-Anomalies ploted on the load cureves

Here the threshold is automatically calculated using the loss function values. But if the calculated value is not fit, a marginally soft threshold value can be fitted manually. The CNN and RNN Autoencoders are yet to be tested on the available online dataset.

6. EXPECTED RESULTS

Demand-side management mechanisms can be designed to control the electric resources of individual users. Using the obtained Load forecast results, currently, the load curve is plotted using the Matplotlib library. Here the red color line is the threshold value assigned to the system manually, or the loss function calculated threshold value is used in the autoencoder. Using python, we can get the line intersection points and obtain the time value. Using those time values, we can schedule some algorithms to shift the workload of unwanted machines to off-peak hours or run the essential machine in energy-saving conditions.

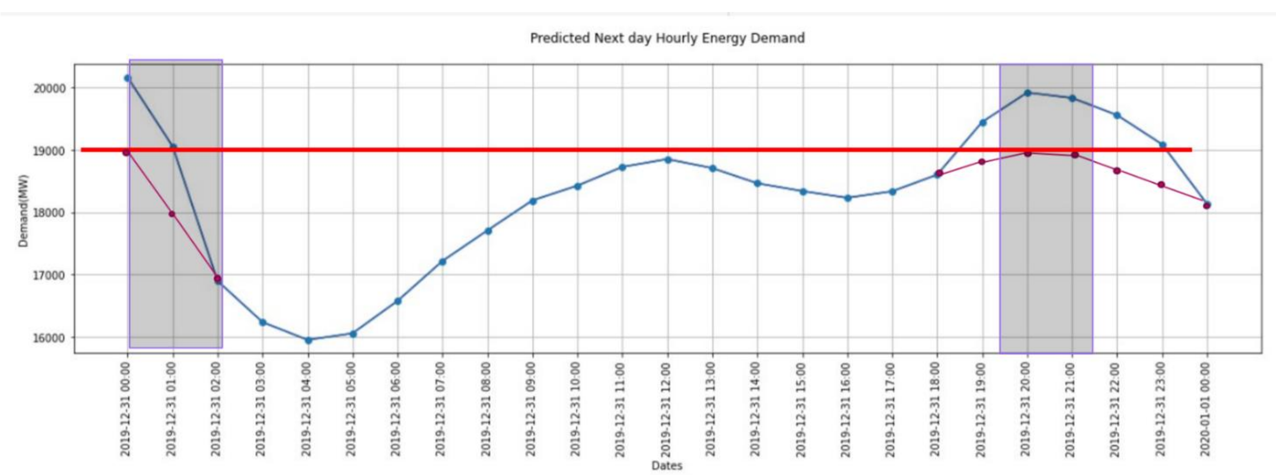

Figure 24- Individual House Demand Curve flatning

According to LSTM, RNN and LSTM model build on the online dataset and obtained R2 score values, the proposed ensemble model will be varied as below-

Table 6- Obtained R2 score value for LSTM, RNN and CNN and expected value for proposed ensemble model

Model	Accuracy (R2 score value)
LSTM	0.93
RNN	0.94
CNN	0.97
Proposed Model	0.93<=exp.val<=0.97

7. FUTURE DIRECTIONS

- Test the proposed ensemble learning model with more Algorithms to obtain higher accuracy and precision. For example, instead of using the pure LSTM model, some other mix models like CNN-LSTM, or Bi-LSTM models can be added to the proposed ensemble learner and check the accuracy score values to verify they are working better than the basic LSTM model. Similarly, there are more modified models with higher accuracy for RNN and CNN. Those also should be tested with the proposed ensemble model for both long-term and short-term predictions.
- Improve the security features of the HEMS. Because usually, every energy management system has a dashboard to view and control. Therefore, HEMS as mission critical system, we need to have more advanced security algorithms and techniques to secure the system. For that, a security layer also should lie between the edge layer and the cloud layer. Following are some key components that are needed to design and implement in the future.

1. Authentication

   Hence, we measured electricity usage through HEMS, no one could not be able to alter the device and data (device authentication). Next, the user who wishes to interact with the system must ensure that he or she is the actual user (user authentication).

2. Authorization

   After the user identity is authenticated, the goal of authorization is to assign specific access rights to each user. For example, there might be different types of users in the HEMS system. They are mainly two users in the system. They are Super users and regular users. Super Users might be the service provider and administrators of the systems. Ordinary and regular users might be electricity consumers. So, both parties have different access rights to differentiate their activities.

3. Intrusion Detection

   Intrusion detection systems (IDS)ensures data security by identify attacks prior to it happen. Hence propose HEMS can be implement on multiple homes, a collaborative IDS is needed that can be work in distributed environment.

4. Privacy

   In the proposed HEMS we collected detail energy and state information. Therefore, middle party could not be able to obtain HEMS users personal details and power consumption details. Hence the privacy of the user must secure using cryptographic technologies.

- Implement more practical solutions for Individual house Demand curve Flatting using proposed HEMS design. Some solutions are listed below.

  - ✓ To solve the problems caused by demand exceeding the supply can be solved in two methods. Those are-

    1. Build more power plants
    2. Use smart grid technology.

Building more power plants is not feasible for a bankcourrpt country like Sri Lanka. Because the available natural resource on the earth is finite and at the moment government cannot spare a huge amount of money for building coal or hydropower plants. On the other hand, coal power plants emitting fume cause air pollution.

- ✓ Even though renewable resources are also much more costly these days there are many researches done using them to build solution for demand curve flattening's Implement a distributed battery backup system and combined renewable energy to power up the high-priority equipment's in peak hours as a future implementation of this system
- ✓ There are many techniques that exist to solve high-demand problems. According to most researchers, the most effective method is to utilize ESS (Energy Storage System) and V2G (Vehicle to Grid). The ESS is a device that stores electricity when the demand is low, and it provides stored electricity when the demand is high. This improves energy efficiency and stabilizes the operations of the electricity grid. The V2G describes a system in which EV (Electric Vehicle) and PHEV (Plug-in Hybrid Electric Vehicle), communicate with the grid to sell demand response services by either transmitting electricity into the grid or by throttling their charging rate [8]. As mentioned above, if we use the ESS and V2G technologies appropriately, the problems caused by peak load can be solved. In Sri Lanka due to the Fuel crisis, people are more interested in buying electric vehicles rather than diesel and petrol vehicles. Therefore, this solution will be more helpful in the future.
- ✓ Implement such algorithms like particle swarm optimization (PSO), Binary particle Swarm Optimization (BPSO), and Linear Programming (LP) algorithms for flattening the demand curve. Because using those algorithms, load shedding and shifting can be done very easily.

- ✓ The next solution is to Control the devices Automatically to reduce usage without shutting down the device completely to reduce the usage and cost. Some electric appliances need to be modified to control their functions remotely to execute this solution. For example, think some appliances like Air conditioners and refrigerators are working in peak demand hours. To reduce the high electricity demand, each device's (Refrigerators, Ovens, Air Conditioner etc.) temperature is controlled to save energy. It might increase the device temperature to 20ºC to 2ºC below room temperature. Likewise, if this method runs in multiple houses, it will immensely help to reduce the demand in peak hours. Nevertheless, doing these for multiple houses will increase the demand in off-peak hours and unstable the grid. Therefore, while shifting the loads to off-peak hours, we have to monitor the total demand curves and their real time variations plotted at the energy generation point (power plant).

8. CONCLUSION

This paper proposed a full architecture of an intelligent home energy management system with load and price forecasting technique. The main objective of this approach is to improve the precision of electricity load and price forecasting model. The proposed forecasting model was an ensemble learner-based, CNN-RNN-LSTM hybrid model with novel optimization technique grid search. Only the LSTM model experiments on a publicly available dataset for residential buildings and developed the LSTM Autoencoder model to identify anomalies in the dataset.

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