International Conference on Recent Trends in Data Science and its Applications
DOI: rp-9788770040723.123

Improved Energy Efficiency in IoT based Smart Energy Meter Reading and Billing System

DikshaNasa
Department of Data Science and Business System, SRM Institute of Science and Technology, Kattankaluthur Campus, Chennai, India.

Parnika Sharma
Department of Data Science and Business System, SRM Institute of Science and Technology, Kattankaluthur Campus, Chennai, India.

Dr. M. Ramprasath,
Assistant Professor
Department of Data Science and Business System, SRM Institute of Science and Technology, Kattankaluthur Campus, Chennai, India

***Abstract*- Each household, industry, or other setting that relies on energy must consider this. It is crucial to manage energy well and conserve it when using appliances.**

To do this, much research has been done to create smart lighting systems for rooms to save energy. In a separate study, researchers created an Internet of Things (IoT)-based Smart Home system to track energy use and ward off anomalies.

Researchers have not attempted to automate appliance control to save energy in any studies. Most of them focus on using android devices to operate the appliances. As a result, we have created an IOT-based Smart Energy Meter system that uses information about light intensity and humidity to remotely operate appliances like Bulb at first. Moreover, the system consistently calculates the appliances' daily energy consumption, giving the user insight of how much energy is utilized over time. Moreover, a bill will be created, and the payment window for bills will be available. The Cloud server is updated with this information. Every family may conserve energy with this prototype method.

Thus, cutting-edge technology like smart energy metres and AI-powered power management have the potential to completely change how we use and manage energy. Smart energy metres allow for real-time tracking and monitoring of energy use, giving consumers precise and in-depth data about their energy usage. Using machine learning algorithms to forecast energy usage trends and improve energy use, power management with AI goes one step further. To gather information from energy meters and send it to a cloud-based server for analysis and invoicing, the system employs Raspberry Pi as its central hub. The device removes the need for human meter readings and provides precise, real-time data to utility providers as well as their consumers. From personal residences to industrial facilities, this technology may be used to minimize waste and boost productivity in a variety of scenarios. People may significantly reduce their energy costs and help create a more sustainable future by implementing AI-powered power management solutions. Overall, smart energy metres and AI-powered power management have the potential to revolutionized how we use energy and contribute to the creation of a society that is cleaner, greener, and more sustainable.

I. Introduction

The increase in economic growth often leads to an increase in the utilization of non-renewable energy resources. This is because the demand for energy often increases as economies grow and become more industrialized. Non-renewable energy resources such as fossil fuels, coal, and natural gas have been the primary sources of energy for many countries due to their abundance and low cost. However, their continued use has led to environmental concerns such as air and water pollution, and the release of greenhouse gases that contribute to climate change. Therefore, it is essential for policymakers to balance the need for economic growth with the need for sustainable energy sources, such as renewable energy, to ensure a cleaner and more sustainable future for generations to come.

The use of Raspberry Pi 3 in various research projects has led to the development of innovative IoT applications for temperature and humidity monitoring, smart home monitoring and control, and energy management. The autonomous temperature and humidity [1] management system developed using Raspberry Pi 3 provides an efficient solution for maintaining a comfortable indoor environment without human intervention. Similarly, the smart house monitoring and control system [2] enables users to remotely control various home appliances and monitor their energy consumption. The automatic room lighting and control system [3] developed using Raspberry Pi and IoT technologies provide users with a convenient way of controlling the lighting and ambiance of a room. Finally, the energy management system for smart houses [4] enables homeowners to manage their energy demand and generation simultaneously, leading to efficient energy usage and cost savings. Overall, the use of Raspberry Pi and IoT technologies has shown great potential in developing innovative solutions for various applications in smart homes and energy management.

Regretfully, no investigation has contributed to the development of a system for controlling the use of electrical appliances based on environmental conditions, which may eventually reduce domestic energy usage. A system like this might incorporate IoT and machine learning to optimise energy use based on environmental factors like temperature, humidity, and illuminance. To create new solutions that make most of cutting-edge technology and tackle the society's rising energy usage issues, more research in this area is required.

Below is the arrangement of the remaining parts. The related work to the research study can be found in Section II.

Our proposed IoT-based system is described in detail in the third part, along with a data flow diagram and a schematic flowchart showing how the entire system operates. The prototype is examined in conjunction with hardware and software design in the fourth step. The recommended structure is covered in Part V, and the metrics are covered in Section VI. Section VII contains a summary of the results and discussions. In section VIII, the conclusion and future work are addressed.

II. Related Work

DOI: rp-9788770040723.123

In recent years, there has been a growing interest in developing smart energy meter systems that can accurately monitor and manage energy consumption in residential and commercial buildings. The emergence of the Internet of Things (IoT) has further enabled the development of such systems by providing the necessary infrastructure for connecting a large number of energy meters to the internet and enabling real-time data analysis.

Machine learning (ML) algorithms have also been extensively used in smart energy meter systems to analyze the large amounts of data generated by these devices and provide useful insights for optimizing energy consumption. In this section, we review some of the relevant literature on IoT based smart energy meter systems with ML.

A study by M.Lavanya et al. (2016) proposed a model that utilizes IOT technology and linux OS along with C++ to import temperature and humidity information. The proposed system sent the data collected via the sensors over the internet. This acts as basis for out project as we utilize the varied sensors to collect light intensity, temperature and humidity readings.

Another study by Wang et al. (2020) proposed an IoT based energy management system that used a combination of deep learning and reinforcement learning algorithms to optimize energy usage in commercial buildings. The proposed system used a deep neural network to learn the energy consumption patterns of the building and a reinforcement learning algorithm to provide optimal control actions for reducing energy consumption. This system utilizes deep learning to understand energy usage patterns and thus, utilize this information to optimize usage of energy resources.

In a study by Kim et al. (2020), proposed a hybrid IoT and machine learning algorithms are used in a cloud-based energy administration system to determine how much energy residential appliances would spend. The system employs smart plugs that monitor energy consumption and send data to a cloud-based server. The data is then analyzed using machine learning algorithms to predict energy consumption patterns for different appliances.This study highlights the potential of machine learning algorithms and IoT technologies in developing innovative solutions for energy management, and further research in this area could lead to significant energy savings and a more sustainable future.

Finally, a study by Gitanjali et al. (2021), proposed an IOT based Smart Electricity Energy Meter system to manage residential energy consumption in smart grid infrastructure. This presented a futuristic and nontraditional approach to traditional energy meters. It provides real-time data and analysis of energy consumption, which can help users to make informed decisions about their energy usage.

Overall, these studies demonstrate the effectiveness of using IoT based smart energy meter systems with ML for optimizing energy usage and reducing energy consumption in residential and commercial buildings.

III. Proposed System Setup

The management of electrical failure dangers and appliance control have been the main areas of attention for existing Smart Home and Energy Management systems. There hasn't been any research that has led to the creation of a system that monitors the environment, adjusts appliance usage as necessary, and warns the user when the humidity level rises. We have developed an IoT-based system that makes use of environmental sensors, such as those for temperature and light intensities, that in turn deliver data to a Raspberry Pi 3. Machine-to-machine communication, often known as IoT, is a recent development. Based on the detected measurements, the Raspberry Pi is set up to manage how much energy is used by the appliance.

In addition to controlling appliance use, the total power consumed by each appliance is calculated on a regular basis and graphed using the DHT11 and communicated to the Raspberry Pi3. In ThingSpeak, there is graphic data showing how time and power use for all appliances operating in various environments relate to one another. This data can then be further utilized to identify insights on consumer consumption habits of energy.

Fig. 1 presents the system design of an IoT-based Energy Management system.Fig. 7 illustrates the Data Flow Diagram (DFD) of the system, which shows the flow of data between different components of the system.Fig. 8 presents the Use Case diagram of the system, which shows the different scenarios and interactions between users and the system.

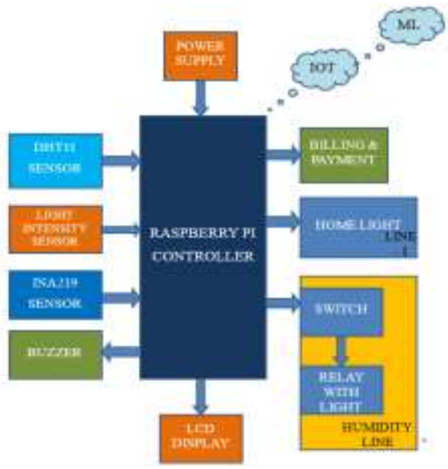


Fig. 1: IoT Based Smart Energy Management System

The DHT-11 SENSOR sensed data are used as the project's initial input (Take temperature and humidity readings) The DHT11 sensor uses a single wire to serially measure and transmit temperature and humidity measurements. It is capable of measuring temperature in degrees Celsius between 0 and 50°C as well as relative humidity (20 to 90% RH) in percentage form. One of its four pins is utilised for serial data transfer.The LDR sensor should then be read for light intensity.

The Raspberry Pi is an inexpensive Linux computer with a set of GPIO (General Purpose Input/Output) ports

DOI: rp-9788770040723.123

that allow you to communicate with electronic devices for computing, physical and scientific Internet of Things (IoT).

Here, if the LDR falls below or equals the threshold (i.e., LDR =40000), "NIGHT TIME" is shown on the display screen, and the LED is switched "ON." Light is produced by a semiconductor device called a light-emitting diode when current flows through it. DHT11 valuations are produced when the energy that was previously stored in the semiconductor's electrons and electron holes is once again released.

The INA219 is essentially a current sensor, it senses current and outputs power and voltage when the LED is on.

A current/power monitoring module with zero drift and bi-directional operation, the INA219-based Current Sensor Module CJMCU-219 uses the I2C interface. It has the ability to simultaneously measure shunt voltage, current, and power and send the information through the I2C protocol. For the purpose of enabling current measurements, it features a 0.1 Ohm, 1% shunt resistor. Its robust 12-bit ADC effectively translates the current measured by a precision amplifier. The resolution is 0.8mA, and the current sensing range is 3.2A.

Fig. 2: Proposed system circuit

Instead, if the LED is not glowing, keep taking measurements and sending them to ThingSpeak. Sending sensor data to the cloud is possible using the IoT Cloud platform ThingSpeak. You may create Internet of Things apps and gather and store sensor data using the Web Service (REST API) that is included. MATLAB, Raspberry Pi, and Arduino are all compatible with it (premade libraries and APIs 18 exists). But, as it makes use of a REST API and HTTP, it ought to be compatible with any programming languages.

Energy is then computed, and a new bill is created. The user's Interface is created using the Tkinter package. Tkinter is the primary GUI Python module. Python along with Tkinter can be employed to create GUI programs quickly and effortlessly. Tkinter is a Python library used for building desktop applications with a graphical user interface. It provides tools for creating windows, buttons, and other widgets to interact with the user. Tkinter offers a sturdy object-oriented gateway for the Tk Modules. To pay a bill via the Twillio API, an SMS is then delivered to the user.

Fig. 3: Day-time output

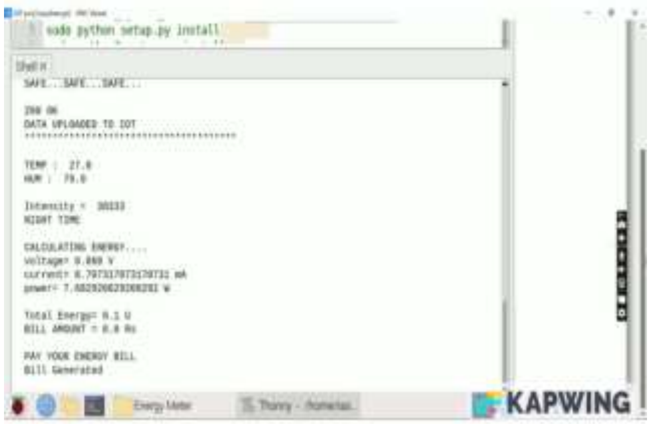


Fig. 4: Night-time output

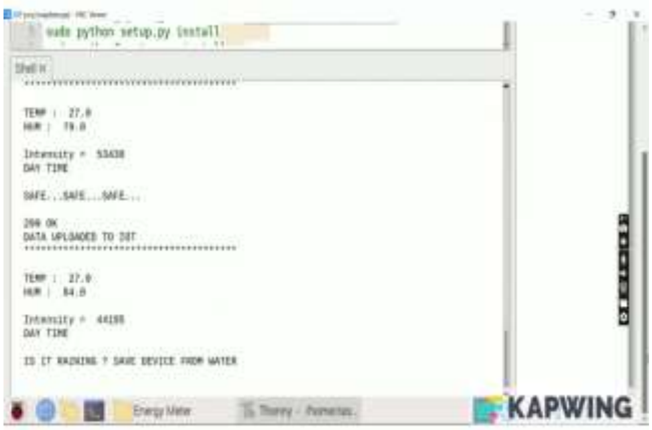


Fig. 5: High Humidity output

Twilio is a cloud communications provider that offers a web API that lets customers create phone, VoIP, and SMS apps using common web languages. As a result, the user is presented with the Graphic User Interface for bill payment.

DOI: rp-9788770040723.123

The programme execution halts upon a successful payment completion.

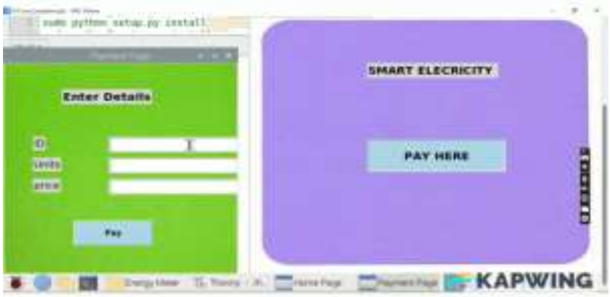


Fig. 6: Bill paying system interface design

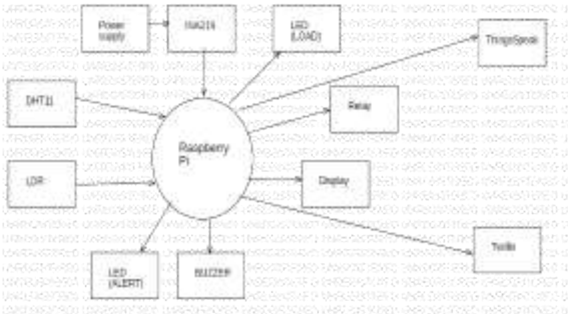


Fig. 7: Data Flow Diagram

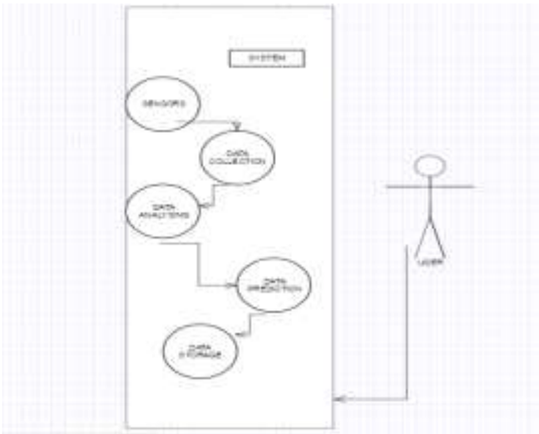


Fig 8: Use Case diagram

IV. Hardware And Software Design

Jumper wires are utilized to link the hardware elements that make up this system. In order to gather data in real time, the temperature sensor and the light intensity sensor are placed into the environment. We haven't utilized 220-volt appliances like fans and lights because we've just created a prototype; instead, we've used computer cooling fans that work on 12-volt batteries and LED lights rather than regular incandescent bulbs. In the explanation that follows each hardware component, the connections that have been made to each component are listed.

A. Humidity and Temperature Sensor

A standardized moisture and temperature sensor that provides a digital output is the DHT11 Sensor. High consistency and outstanding long-term consistency are ensured by this sensor. This sort of sensor connects to an 8-bit CPU and incorporates NTC temperature detection and resistivity-type measuring components. As a result, it offers good quality, rapid response, interruption resistance, and economic feasibility.

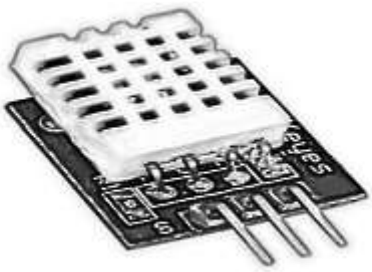


Fig. 9: DHT11 sensor

B. Light Dependent Resistor

An electrical component that reacts to light is referred to as a photoresistor, sometimes known as a light-dependent resistor. As light strikes it, the resistance modifies. When light intensity rises, the LDR's resistance decreases, shifting by orders of magnitude. A typical LDR or photoresistor's resistance value falls between a few megaohms in total darkness to a few hundred ohms under bright light. An LDR sensor is a type of sensor that uses a Light Dependent Resistor to detect changes in light intensity (LDR). It is frequently employed in electrical devices to determine whether light is present or not. Automatic streetlights, security systems, and camera light meters are just a few of the numerous uses for LDR sensors.

Fig. 10: Light Dependent Resistor

C. Raspberry pi

The Raspberry Pi Foundation, which is headquartered in the UK developed a series of compact single-board computers designated as Raspberry Pi. These computers are preferred by professionals, academics, and hobbyists because of their minimal cost, efficiency, and great extent of customization options.

The Raspberry Pi boards are built around an ARM-based processor and run on a variety of operating systems, including the popular Linux-based Raspbian OS. They feature a variety of input/output options, such as USB, HDMI, Ethernet, and GPIO pins, which allow users to connect and interact with a wide range of devices and sensors.

Overall, Raspberry Pi offers a low-cost and flexible platform for users to experiment with and build their own custom computing solutions. It has become a popular tool for both learning and prototyping in the fields of computer science, engineering, and maker culture.

DOI: rp-9788770040723.123

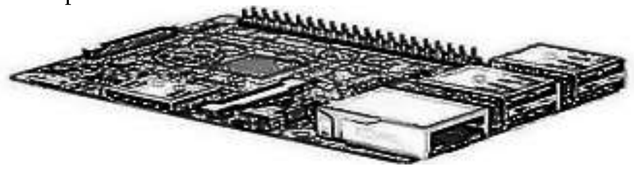


Fig. 11: Raspberry pi

D. LED

A semiconductor device termed as an LED (which stands for "Light Emitting Diode") emits photons when an electrical current travels through it. Due to its energy effectiveness, extended durability, and potential to create a wide spectrum of colors, LEDs are commonly utilized as light sources. They are used in a variety of applications, such as backlighting for electronic displays, residential and commercial lighting, and automotive lighting. LEDs are also widely used in research settings for their controllability and versatility in producing specific wavelengths of light. This makes them useful for studies involving plant growth, circadian rhythms, and phototherapy. LEDs are a popular choice for researchers due to their low heat output, long lifespan, and low power consumption.

Fig. 13: LED

E. INA 219 SENSOR

The INA219 sensor is a high-precision, low-cost, digital current and voltage sensor that is widely used in research applications. It can measure voltage levels up to 26V and current up to 3.2A with an accuracy of up to 1%. The sensor can communicate with a variety of microcontrollers using I2C or SMBus protocols, making it easy to integrate into electronic systems. Its small size and low power consumption make it an ideal choice for portable or wearable devices. Researchers use the INA219 sensor in a range of applications, such as battery monitoring, power management, and solar energy systems, due to its high accuracy and reliability.

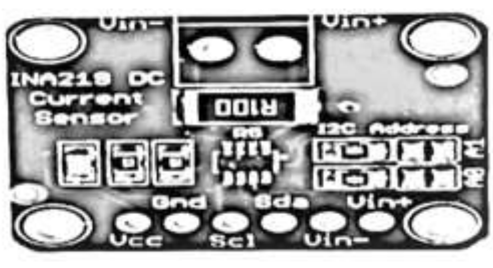


Fig12: INA219 Current Sensor

F. ThingSpeak

ThingSpeak is an open-source Internet of Things platform that allows users to gather, evaluate, and display data from Internet of Things devices. It allows users to store and retrieve data in real-time and provides tools for data analysis, visualization, and alerting. ThingSpeak supports a wide range of IoT devices, such as sensors, actuators, and microcontrollers, and integrates with other popular IoT platforms and services. It also provides APIs for easy integration with other applications and data sources. ThingSpeak is popular among IoT enthusiasts, researchers, and businesses for its ease of use, flexibility, and affordability. It has numerous applications in various domains, such as agriculture, smart homes, industrial automation, and healthcare.

G. Tkinter Module

Tkinter is a Python module for building graphical user interfaces (GUIs) for desktop applications. It provides an assortment of widgets and tools for making panels, icons, labels, checkboxes, and other GUI aspects, allowing users to interact with the application through a graphical interface. Tkinter is easy to learn and widely used in Python development for creating simple to complex GUI applications.

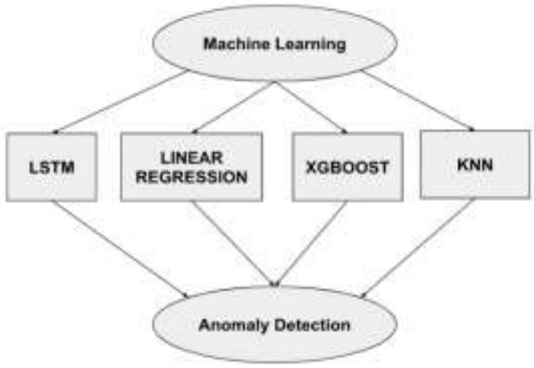
H. Twillio Module

Twilio is a cloud communications platform that enables businesses to build communication solutions using APIs for voice, video, messaging, and authentication. It allows programmers to incorporate communication tools into their apps, including the capacity to send and receive SMS messages, place and attend video as well as audio conversations, and implement two-factor authentication to confirm credentials of a particular user. Twilio's platform is designed to be easy to use and scalable, allowing businesses of any size to build and deploy communication solutions quickly and efficiently.

Twilio's APIs support multiple programming languages, including Python, Java, Ruby, and Node.js, making it accessible to developers with various programming backgrounds. Twilio also provides a range of tools and services to help businesses manage their communication solutions, such as analytics and reporting, debugging and testing, and security and compliance.

V. PROPOSED FRAMEWORK

A subset of artificial intelligence (AI), known as machine learning (ML), enables computers to dynamically learn from data and previous experiences in order to recognize patterns and forecast future happenings with the least amount of human intervention.



DOI: rp-9788770040723.123

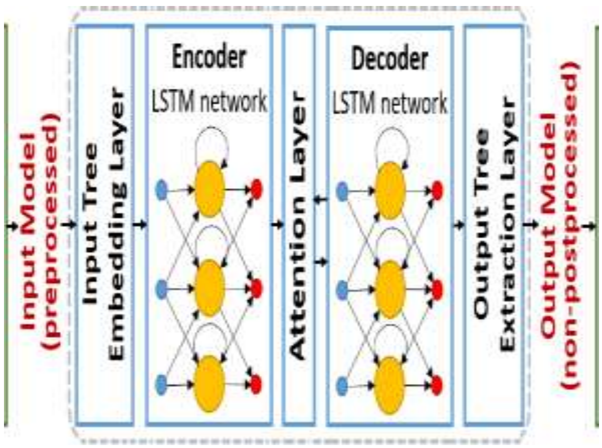
For our project, we have used various types of ML modules and algorithms. Those maybe explained as follows:

A. LSTM

Long Short-Term Memory, often known as LSTM, is a form of recurrent neural network (RNN) that can process and retain sequential input.

Each unit in a typical RNN receives the output of the unit before it as well as the current input. A cell, an input gate, an output gate, and a forget gate make up each unit of LSTMs, which are more sophisticated. The network is able to selectively forget or recall knowledge from the past thanks to these gates, which control the flow of information into and out of the cell.

In our project, LSTM is utilized to predict the values of power and energy. The model takes into account the data collected in the form of a time series, effectively capturing long-term dependencies in sequential data. Thereafter, utilizing this model to predict the sequential values of power and energy.



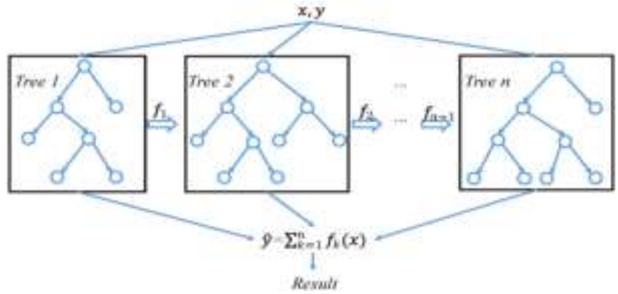
Architectural Diagrammatic Representation

B. XGBOOST

A well-known open-source machine learning toolkit called XGBoost is used to train gradient boosting decision trees. The Apache Software Foundation is currently responsible for maintaining it once it was created in 2014. It may be executed in parallel on a number of CPUs or GPUs and is made to handle huge datasets. Advanced features including regularization, cross-validation, and early halting are included. Several applications, including image classification and financial forecasting, have successfully exploited XGBoost.

XGBoost can be used for time series forecasting tasks by treating the time series as a sequence of input-output pairs. Specifically, one can create a window of lagged values from the time series as features and use the next value as the target variable.

In the context of our system, XGBOOST presents a negative pipeline score depicting that this is not a good fit for our data. One possible reason for negative accuracy values is that the model is predicting values that are far from the actual values, resulting in a large error. This can happen if the model is not able to capture the temporal dependencies.



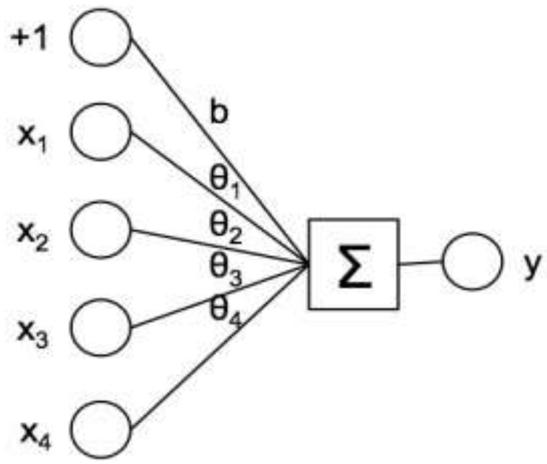
Architectural Diagrammatic Representation

C. Linear Regression

By utilizing linear regression, one may statistically simulate the relationship across a dependent variable and one or more independent variables It makes the assumption that the variables' relationships are linear and can be shown by a straight line. The approach, which may be applied to both simple and multiple regression analysis, estimates the parameters of the line that fits the data the best. In various disciplines, such as economics, social sciences, and engineering, linear regression is frequently used to forecast or explain the dependent factor's activity depending on the values of the independent factors.

In our project, linear regression presents a very good accuracy score of 1.0, which presents that the data fits the model perfectly.

This portrays that the relationship between temperature, humidity, light intensity is linearly associated with energy.



Architectural Diagrammatic Representation

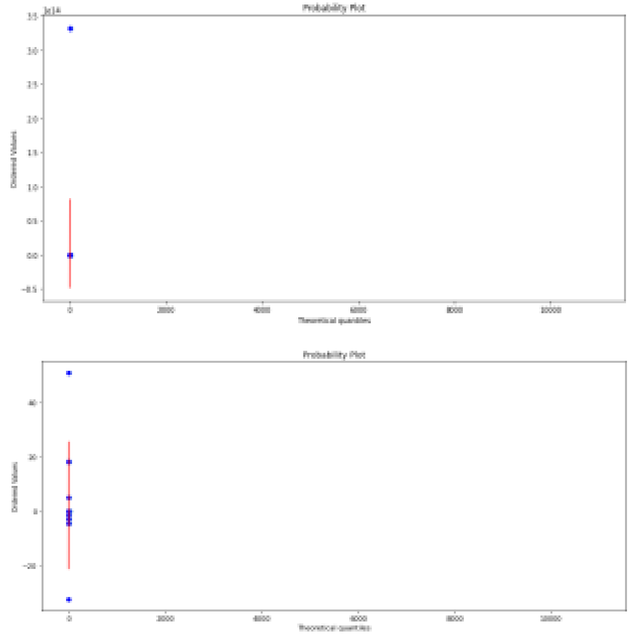
D. KNN

To addrss issues with regression and classification, K-Nearest Neighbors (KNN), a non-parametric machine learning methodology, is employed. It functions by determining the K data points that are the nearest to a certain sampling point, and then using the titles or valuations of those K nearest neighbors, estimates the label or valuation of the test point. The number of neighbors to take into account is determined by the value of the hyperparameter K. KNN is easy to comprehend and put into practice, but it can be computationally costly for big datasets and is susceptible to the distance measure chosen.

In our project, KNN presents a negative score, indicating that our data is not a good fit for the model. This

DOI: rp-9788770040723.123

maybe caused as our data is a time series data and KNN does not consider the temporal order of the data. Hence, implying that the model is not able to capture the patterns or trends in the time series data.



Architectural Diagrammatic Representation

Unlike models built using deep learning, K-Nearest Neighbors (KNN) is a straightforward non-parametric method for machine learning without a preconceived framework.

E. *Anomaly Detection*

A method used in data analysis called anomaly detection seeks out patterns or occurrences that are strange or unexpected. The objective is to find anomalies that considerably vary from the data's expected behaviour since they may be signs of significant occurrences or problems. Applications including fraud detection, intrusion detection, and predictive maintenance frequently employ anomaly detection.

One-class Support Vector Machines (SVM) is a popular algorithm used for anomaly detection. In this approach, the goal is to identify anomalies as points that are significantly different from the normal behavior of the data. One-class SVM learns a boundary that separates the normal data points from the anomalous ones.

It works by fitting a hyperplane in a high-dimensional feature space and then identifying the observations that lie on the boundary or outside it. The algorithm only requires a training set of normal data to learn the hyperplane, and then uses it to classify new observations as normal or anomalous. One-class SVM is effective when there is limited or no prior information about the anomalous data and when the normal data points are clustered together. It is also computationally efficient and can handle high-dimensional datasets. However, it can be sensitive to the choice of parameters and may not perform well when there is a significant overlap between the normal and anomalous data points.

In case of our project, 4 anomalous outliers are detected using One class SVM. These values of power and energy deviate from the other values.

```
# filter outlier index
outlier_index = where(y_pred == -1)
# filter outlier values
outlier_values = df_train.iloc[outlier_index]
outlier_values
```

	Power	Energy
14	275.121951	2.751220
97	22.682927	0.226829
98	22.682927	0.226829
99	22.682927	0.226829

VI. METRICS

A. *LSTM*

Recurrent neural networks (RNN) incorporate Long Short-Term Memory (LSTM) that is especially made to handle sequential data, including time series, voice, and text. Language translation, speech recognition, and time series forecasting are just a few of the applications for LSTM networks, which have the ability to learn long-term relationships in sequential data.

The "model.evaluate()" method calculates the loss and evaluation metrics for a trained model on a given test set.

Formula: -

accuracy = (number of correct predictions) / (total number of predictions)

*MSE = (1/n) * Σ(yi - ŷi)^2*

Accuracy Score: 91.6 %

Result:

Thus, in our project, the values of power and energy are predicted using LSTM. The model effectively accounts for long-term dependency in sequential data because it takes into account data collected as a time series. The subsequent levels of power and energy may then be predicted using this model.

B. ***XGBOOST***

Extreme Gradient Boosting, or XGBOOST as it is known, is a concept put out by University of Washington academics. It is a C++ library that enhances the training process for gradient boosting. Moreover, this model does not fit our product well.

The pipeline.score() method for an XGBoost model may be used to assess how well the trained model performed on a test set. The approach returns either the coefficient of determination R2 of the predictions for regression problems or the mean accuracy of the predictions for classification issues.

Formula: -

R^2 = 1 - (sum of squared errors / total sum of squares)

Accuracy Score: XGBoostregressor

DOI: rp-9788770040723.123

r2: -0.26916466699066377

Result:

A negative pipeline score from XGBOOST in the context of our system indicates that this is not a suitable fit for our data. One explanation for low accuracy numbers is because the model is making huge errors by predicting values that are quite different from the actual values. If the model is unable to account for the temporal dependencies, this may occur.

C. KNN

By averaging the data in the same neighbourhood, the non-parametric KNN regression method roughly captures the link between independent factors and the continuous outcomes. For our project, this model's accuracy is subpar.

Primarily, the k-nearest neighbour classification algorithm depends on a distance function. The more precisely that measure captures label consistency, the more efficient the classification. The Minkowski distance is the most popular pick.

Formula:

dist(x,z)=(∑r=1d|xr−zr|p)1/p.

accuracy = (number of correctly classified samples) / (total number of samples)

Accuracy Score: -0.08425501126153923

Result:

KNN provides a poor score in our project, suggesting that the model does not suit our data well. This could be the result of the fact that our data is a time series and KNN does not take the temporal order of the data into account. So, it is implied that the model is unable to fully represent the patterns or trends present in the time series data.

D. Linear Regression

Linear regression is a supervised learning-based method of machine learning.

A regression procedure is carried out. Regression models a specific prediction value using independent variables. It is mostly used to establish the connection between parameters and forecasts. The number of independent variables they use and the kind of relationship they take into consideration between the dependent and independent variables are two ways that regression models differ from one another. The low score shows that the project's variables do not relate to one another linearly and that the model does not match the data well.

The R2 score, commonly referred to as the coefficient of determination, is calculated by scikit-learn's.score method for linear regression models. The linear regression model's ability to fit the data is shown by the R2 score.

A better match is indicated by higher values, which range from 0 to 1.

Formula:

R^2 = 1 - (SSres / SStot)

whereSSres is the sum of the squared residuals (the difference between the actual and predicted values) and SStot is the total sum of squares (the difference between the actual values and the mean of the dependent variable).

The formula for multiple linear regression is:

*y = β0 + β1*x1 + β2*x2 + ... + βn*xn + ε*

where:

y is the dependent variable (also known as the response variable)

x1, x2, ..., xn are the independent variables (also known as the predictor variables)

β0, β1, β2, ..., βn are the coefficients (also known as the regression coefficients or model parameters) that represent the change in y for a one-unit change in x1, x2, ..., xn, holding all other variables constant

ε is the error term, which represents the variability in y that is not explained by the independent variables.

Accuracy Score: 1.0

E. Anomaly detection

Anomaly identification, also known as outlier detection, is an approach for uncovering unexpected occurrences, observations, or occurrences that deviate considerably from the usual. Unsupervised anomaly detection is a technique used by data scientists to spot anomalies in unlabeled data, and it is based on the following two vital hypotheses:

Data anomalies are uncommon occurrences with unique characteristics that set them apart from regular occurrences..

Formula:

An approach to finding odd patterns or occurrences in data is called anomaly detection. Although there are various ways to perform anomaly detection, the Gaussian distribution-based technique is one that is frequently utilized.

The following is the formula for anomaly detection using the Gaussian distribution-based method:

i. Estimate the mean and covariance matrix of the features in a dataset X.

ii. Calculate the chance that each observation x in X falls within the Gaussian distribution that is indicated by the estimated mean and covariance matrix.

iii. The probability below which an observation is regarded as an anomaly should have a threshold value. The threshold value might be selected using a validation set or based on prior knowledge about the problem.

Determine the observations that fall below the threshold in terms of likelihood to be anomalies.

The following formula may be used to determine the likelihood that an observation x will fall inside the Gaussian distribution denoted by the estimated mean and covariance matrix:

*p(x) = (1 / (2π)^n/2 * |Σ|^1/2) * exp(-1/2 * (x - μ)^T Σ^-1 (x - μ))*

DOI: rp-9788770040723.123

where:

n is the number of features in x
μ is the estimated mean of the features in X
Σ is the estimated covariance matrix of the features in X

The intended trade-off between false positives and false negatives can be used to determine the threshold value. In contrast to a low threshold number, which will produce more false positives but fewer false negatives, a high threshold value will produce fewer false positives but more false negatives.

The SVM method known as One-Class Support Vector Machines (OCSVM) is used to find anomalies. One-Class SVM's formula is as follows:

Let's say we have a collection of observations X, each of which is a vector of p characteristics. Finding a function f(x) that maps the data to a one-dimensional space with normal observations being mapped to values near to 1 and anomalous observations being assigned to values noticeably below 1 is the objective.

The optimization problem for one-class SVM is formulated as follows:

*minimize (1/2) * ||w||^2 + (1/nu) * sum(xi - rho)*

subject to yi*f(xi) >= 1 - epsilon, for all i

where:

w is a vector of weights
xi is the ith observation in the training set
rho is a scalar offset parameter

yi is a binary variable that indicates whether xi is a normal observation (+1) or an anomaly (-1)

f(xi) is the distance from the decision boundary to xi

epsilon is a small positive parameter that controls the width of the margin around the decision boundary

nu is a hyperparameter that controls the tradeoff between the width of the margin and the number of training observations that are allowed to be misclassified as anomalies

The optimization problem seeks to find the weights w and the offset parameter rho that minimize the objective function subject to the constraints. The decision function for a new observation x is given by:

*f(x) = sum(alpha_i * K(x_i, x)) - rho*

where:

alpha_i are the coefficients of the support vectors

K(x_i, x) is a kernel function that measures the similarity between x_i and x

If the value of f(x) is less than a threshold, the observation is classified as an anomaly; otherwise, it is classified as normal. The threshold can be chosen based on the desired tradeoff between false positives and false negatives.

Accuracy score: No accuracy rating is available. As an output for power and energy, we received outliers.

Results:

Using one class SVM, 4 anomalous outliers are found in our project. These energy and power values differ from the other values.

VII. Result And Discussion

Dataset: The dataset utilized in this paper for the training and testing was collected using the raspberry pi apparatus and stored in the cloud environment of ThingSpeak. The detailed description of the dataset is presented as follows:

Features	Description
Created_at	A variable that marks the time and date of a particular entry of a data.
Entry id	Variable that contains a specific and unique id of an entry.
Temperature	This variable stores the real-time **temperature reading** collected from the DHT11 sensor.
Humidity	This variable stores the real-time **humidity reading** collected from the DHT11 sensor.
LDR	This variable stores the real-time **light intensity reading** collected from the LDR sensor.
Power	A variable that contains the power calculated.
Energy	A variable that stores the energy hence calculated.

Accuracy:

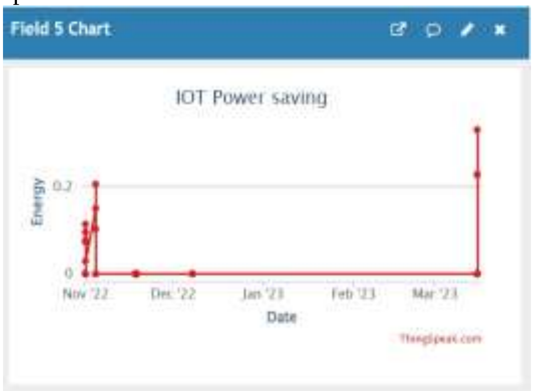
Positive accuracy

Model Name	Accuracy Score
LINEAR REGRESSION	1.0
LSTM	0. 91666668

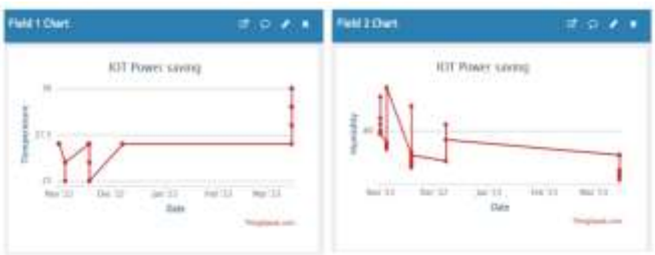
Negative accuracy

Model Name	Accuracy Score
KNN	-0.08425501126153923
XGBOOST	-0.26916466699066377

International Conference on Recent Trends in Data Science and its Applications
DOI: rp-9788770040723.123



Graph demonstrating energy utilization



Graph demonstrating temperature and relative humidity

LDR and power graph

The data presented in the above graphs illustrates the potential benefits of utilizing IoT analytics services, such as ThingSpeak, in energy management systems. Using real-time big quantities of information in the cloud to collect and analyse, energy providers can gain valuable insights into energy consumption patterns and make more informed decisions regarding energy management.

As can be observed from the graphs, there is a correlation between environmental conditions, such as temperature, humidity, and light intensity, and power utilization. A minimal amount of electricity is used during times of elevated temperature, dampness, and light levels, whereas a larger proportion is utilized under opposite situations. This correlation may be attributed to the fact that when the intensity of light rises, the requisite LED intensity drops, requiring less electrical power to function.

Overall, these findings have significant implications for energy management systems. By utilizing IoT technologies and data analytics tools such as ThingSpeak, energy providers can develop more energy-efficient systems, reduce energy consumption, and ultimately reduce their environmental impact. Additionally, these technologies can enable households to monitor and manage their energy usage, potentially resulting in cost savings and a more sustainable energy future.

VIII. Conclusion And Future Work

The proposed smart energy meter system for household management, utilizing a Raspberry Pi CPU, is a significant step forward in energy consumption monitoring and management. By providing a means to monitor and regulate energy use, this system can increase awareness of energy consumption and promote energy-conscious behaviour.

With the ability to modify the power status of devices according to user requests, this system offers a more personalized approach to energy management, enabling users to make informed decisions about their energy usage. By reducing energy consumption, households can lower their environmental impact and save on energy costs.

In this period of swift technological advancement, incorporating intelligent energy metres in household monitoring systems is of the utmost importance. As the demand for energy continues to increase, it is imperative to find ways to reduce energy consumption and promote sustainability. By utilizing IoT technologies and data analytics tools, such as the proposed smart energy meter system, households can play an active role in reducing their energy consumption and contributing to a more sustainable future.

The results of our study demonstrate that a smart energy meter system can be utilized to aid in saving power and energy. The conjugation of machine learning with IOT has become a popular research topic in recent years. IoT devices are capable of generating vast amounts of data, while ML algorithms have the ability to analyze this data and extract meaningful insights from it. When combined, IoT and ML can be used to create intelligent systems that can improve efficiency, reduce costs, and optimize performance. In our study we find that few ML models can with good accuracy utilize the environmental data to predict power and energy usage which can thus aid in optimizing usage of energy resources. While, some models like KNN and XGBOOST do not fit the data. Additionally, the proposed model also utilizes twilio to send user SMS of the bill generated by the system also providing the user GUI presented using Tkinter to pay the bill. An additional feature of high humidity detection is added to alert the user in case of higher concentration of water in the environment inorder to save the device as this may damage the parts involved.

There are several avenues for future research in this area. One direction for future work is to explore the scalability of our proposed system. While our system demonstrated promising results in a controlled laboratory environment, it is important to assess its performance in real-world scenarios with larger datasets and more complex systems. Additionally, further investigation is needed to optimize the performance of the ML algorithms used in our system, as well as to explore the potential of alternative algorithms that may be better suited to the specific requirements of different applications. Another area for future research is to investigate the potential impact of our system on energy savings and sustainability, and to conduct

DOI: rp-9788770040723.123

a cost-benefit analysis to assess the economic feasibility of implementing the proposed system. Finally, we also suggest the development of a theft detection system for the proposed model. Overall, there is significant potential for future research in this area, and we believe that continued investigation and refinement of our proposed system will lead to improved energy efficiency and significant cost savings for organizations as well as households.

In conclusion, our study has demonstrated the effectiveness of our proposed approach for solving the problem of efficiently utilizing energy. Through the use of IOT and ML, we were able to collect real time data using IOT and utilize this with ML to improve the utilization of energy resources. Our study contributes to the field of IOT and machine learning by presenting the future potential of using these technologies to aid in smart energy systems for industrial as well as household purposes. These findings have important implications for the environment and depleting energy resources in the world. While our study has several limitations, including limited dataset, processing power and anomalous readings, we believe that our proposed approach provides a promising solution to the problem of inefficient use of energy. Future research in this area should focus on scaling and adding additional features such as theft detection and API for users to directly pay the bill. Overall, our study highlights the potential of conjugation of IOT and ML to improvise utilization of energy resources by using environmental data, and we hope that our findings will inspire further investigation and innovation in this field.

References

[1] M. Lavanya, P. Muthukannan, Y.S.S. Bhargav, and V. Suresh, “IoT Based Automated Temperature and Humidity Monitoring and Control”, Journal of Chemical and Pharmaceutical Sciences ISSN: 0974-2115.

[2] AbhijeetRajurkar, OnkarShinde, VinayakShinde, and BhushanWaghmode, “Smart Home Control and Monitor System Using Power of IoT’s”, International Journal of Advanced Research in Computer and Communication Engineering, vol. 5, issue 5, May 2016.

[3] Milosevic, Milos, Cetic, Nenad, Kovacevic, Jelena, Andjelic, and Tihomir, “Lighting control using Raspberry Pi and OBLO living home automation system,” Serbian Journal of Electrical Engineering, vol. 16, pp. 45-54, 2019. 10.2298/SJEE1901045M.

[4] ShamikaKshirsagar, and Mr. D.E. Upasani, “Energy Management System for Smart Home”, International Research Journal of Engineering and Technology (IRJET), vol. 03, issue: 06, June-2016.

[5] Gill, Khusvinder, Yang, Shuang-Hua, Yao, Fang, Lu, and Xin, “A ZigBee-Based Home Automation System. Consumer Electronics, IEEE Transactions on, vol. 55, pp. 422 – 430, 2009. 10.1109/TCE.2009.5174403.

[6] Tkinter, https://wiki.python.org/moin/TkInter

[7] Rajesh, M., &Sitharthan, R. (2022). Image fusion and enhancement based on energy of the pixel using Deep Convolutional Neural Network. Multimedia Tools and Applications, 81(1), 873-885.

[8] R. Jiang, R. Lu, C. Lai, J. Luo, and X. Shen, “Robust group key management with revocation and collusion resistance for scada in 5 978-1-5386-4769-1/18/$31.00 ©2018 IEEE smart grid”, IEEE Globe ommunication Conference (Globecom), pp. 824-829, 2013

[9] Hao-wei Yao, Xiao-wei Wang, Lu-sen Wu, Dan Jiang, TengLuo, and Dong Liang, “Prediction method for Smart Meter Life Based on Big Data”, Procedia Engineering, vol. 211, pp. 1111–1114, 2018.

[10] R. Pereira, J. Figueiredo, R. Melicio, V.M.F. Mendes, J. Martins, and J. C. Quadrado, “Consumer energy management system with integration of smart Meters”, Energy Reports, vol. 1, pp. 22–29, 2015.

[11] Soma ShekaraSreenadh Reddy Depuru, Lingfeng Wang, and Vijay Devabhaktuni, “Smart meters for power grid: Challenges, issues, advantages and status,” Renewable and Sustainable Energy Reviews, vol. 15, pp. 2736– 2742, 2011.

[12] Maitra S, “Embedded energy meter – a new concept to measure the energy consumed by a consumer and to pay the bill”, Joint International Conference on Power System Technology and IEEE Power India Conference. pp. 1–8, 2008.

[13] J. Every, L. Li, and D.G. Dorrell, “Leveraging smart meter data for economic optimization of residential photovoltaics under existing tariff structures and incentive schemes,” Appl. Energy, vol. 201, pp.158 - 173, 2017.

[14] Y.K. Penya, O. Kamara, and A. Pena, “IEC60870 meter smart SOA Management”, IEEE PES Innov. Smart Grid Technol, pp. 1-7, 2011.

[15] H. March, A.F. Morote, A.M. Rico, and D. Sauri, “Household smart water metering in Spain: Insights from the experience of remote meter reading in Alicante,” Sustainability, vol. 9, pp. 1-18, 2017.

[16] S. Bayram, and T.S. Ustun, “A survey on behind the meter enegy management systems in smart grid," Renew. Sustain. Energy Rev., vol. 72, pp. 1208 - 1232, 2017.

[17] C. Michael Lorek, Fabien Chraim, and S.J. Kristofer Pister, “PlugThrough Energy Monitor for Plug Load Electrical Devices,” IEEE conference on Sensors, pp. 1 - 4, 2015.

[18] Md. Masudur Rahman, Noor-E-Jannat, Mohd. Ohidul Islam, and Md. SerazusSalakin, “Arduino and GSM Based Smart Energy Meter for Advanced Metering and Billing System”, Int. Conf. on Electrical Engineering and Information & Communication Technology (ICEEICT), Jahangimagar University, Dhaka-I Bangladesh, pp. 1-6, 2015.

[19] Suresh Sankaranarayanana , Au ThienWanb , and Aida HarayaniPusac, “Smart Home Monitoring using Android and Wireless Sensors”, I.J. Engineering and Manufacturing, vol. 2, pp. 12-30, 2014.

[20] S. Suresh, H.N.S Anusha, T. Rajath, P. Soundarya, and V. Prathyusha, “Automatic Lighting and Control System for Classroom”, Proceedings of 2016 IEEE International conference on ICT in Business, Industry and Government, Indore, Madhyapradesh, pp.1-6, 2016.

[21] K. Vinaysagar, and S. Kusuma, “Home Automation Using Internet of Things”, International Research Journal of Engineering and Technology (IRJET) vol. 02, issue: 03, June-2015.

[22] Ms. HlaingThidaOo, Dr. Khin Than Mya, and Ms. NyainNyainLwin, “IoT based Home Energy Management system for Rural Area in Myanmar”, ICT Virtual Organization of ASEAN Institutes and NICT ASEAN IVO Forum 2016.

[23] Diya Elizabeth Paul, and Prof. Alpha Vijayan, “Smart Energy Meter Using Android Application and GSM Network”, vol. 5, issue 03, pp. 16058 – 16063 March, 2016.

[24] Dinesh Thanth, and Mr.AmolBorole, “Wi-Fi Based Smart Energy Meter”, vol. 4, issue 4 , April 2015.

[25] BirendrakumarSahani, Tejashree Ravi, AkibjavedTamboli, and RanjeetPisal, “IoT Based Smart Energy Meter”, vol. 04, issue 04, Apr -2017.

[26] Shaik Salman siddiq, ShaikReshma, K. Anuja, P. Priyanka, and Ch. Karunapravaha (Asst. Prof.), “Smart Electricity Meter using Wi-Fi”, vol.5, no.3, March 2017.

[27] D.Y.R. Nagesh, J.V.V. Krishna, and S.S. Tulasiram, “A Real-Time Architecture for Smart Energy Management,” in Innovative Smart Grid Technologies (ISGT), pp. 1 - 4.53, Jan. 2010.

[28] G. Deconinck, B. Delvaux, K. De Craemer, Z. Qiu and R. Belmans, “Smart Meters from the angles of consumer protection and public service obligations,” in Intelligent System Application to Power Systems (ISAP), pp.1-6, 2011.

[29] Pazhani. A, A. J., Gunasekaran, P., Shanmuganathan, V., Lim, S., Madasamy, K., Manoharan, R., &Verma, A. (2022).Peer–Peer Communication Using Novel Slice Handover Algorithm for 5G Wireless Networks.Journal of Sensor and Actuator Networks, 11(4), 82.

[30] Briot, Jean-Pierre, Hadjeres, Gaetan, Pachet, and Francois, “Deep Learning Techniques for Music Generation - A Survey”, 2017.