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Adapting Internet of Things and Neural Network in Modelling Demand Side Energy Consumption and Management

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Keywords

DAC
Electrical Energy
Machine Learning
MATLAB
Sensor Node

Abstract

With the recent application of micro-grid system and off-grid renewable energy power system using internet of things (IoT) for the efficacy in demand side consumption management. The study employed usage of IoT supported with statistical initiative (logistic regression) to develop a knowledge-based solution for energy demand side consumption management. The research adopted two approaches to model the energy consumption pattern of a user with designed sensor nodes for environmental data acquisition (DAC) monitoring and state of switches (load points). Leveraging on Internet of Things, the sensor node network transferred synchronized the data collected to Google Firebase cloud storage in real time. The data collected were used to train a logistic regression model for the prediction states of the receptacles and sensor readings. The study further investigated power usage (user) against human presence and hour (period) of the day separately and a mathematical model of the relationship was developed. The results revealed customer's energy consumption; this includes models for the future projection. The model can be deployed to predict energy management on the demand side efficiency and availability indices. The models could support energy management including receptacle automation prediction and wastage monitoring.

1. Introduction

The parties involved in energy management are the supplier and the consumer. For adequate and efficient system, it is essential to monitor electrical energy supplied against waste and losses. Misappropriation of energy occurs in the demand side such as public places and this includes offices, classrooms, and laboratories; and even in homes. It is common to find devices on and consuming power even when they are not in use. Detecting state of the receptacles could be based on some user's data; controlling saved energy is the motivation behind this research. The definition for the end users' role of consumer in managing electrical energy on the demand side is termed Demand-Side Management (DSM) [1].

The paper adopted use of Internet of Things (IoT) concept and initial knowledge on data acquisition (DAC) collection of data through sensor nodes and appropriate remote storing system in Google Firebase cloud. The research employed Machine Learning, Logistic Regression model to investigate performance of Demand-Side Energy Management. The concept presented in this paper is called Smart Demand-Side Management (SDSM); this is defined as a form of energy management at the demand side that makes use empirical data and support decision system (DSS) to predict and manage future consumption of energy.

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Different machine learning models have been applied in energy management [2]; including adoption of applied logistic regression in managing load allocation for a central air-condition system for a building [3-5] supported with Artificial Neural Network (ANN) to model a load forecasting system with algorithm-based machine learning system [6]. ANN Could be deployed to model non-linear control system according to the work of [7-8] as presented in applications of neural networks in renewable energy problems solving. Many industries adopt artificial intelligence to learn from customers' data to address organizational gap and improve system availability towards innovations [9-11].

The proposed SDSM system incorporates a form of home automation to controls the load points through learning algorithm, which has to be trained using empirical ambient condition (temperature, pressure, and light intensity) data; this includes, human presence and previous control pattern of the load points by the user as input features. The works in self-decision (smart system), such that if a load point is on in an unusual circumstance, the system can prompt the user and put the load point off, in order to avoid wastage of electrical energy. The previous forms of home automation system merely introduce convenience of control as stated by [12-14]. This paper contributes to existing works by proposing the SDSM system, which improves by the introduction of decision, supported learning algorithm that can initiates hand-free control.

Some previous works has considered knowledge-based approach through use of Artificial Neural Network 1 researched on a system that automatically schedules and coordinates the usage of electricity generated from local energy sources. This could be employed in local PV energy generation, an electricity storage system towards grid efficiency. According to [15], a smart energy management system (SEMS) can be used to optimize grid operation micro view. The study complimented by [16] using temperature and wind velocity as input information for prediction through artificial neural network (ANN) to maximize power generation base on the current (I) values of the input parameters. Furthermore, [17] used Artificial Neural Network to map the non-linear relationship between the load levels of zone and system topologies in the distribution systems. Comprehensive studies by [3-5] used Artificial Neural Network for load forecasting in their respective works. This study replaced ANN with use of Logistic Regression model for efficiency towards have high performance in classification modeling for the size of the collected sensor data set.

Logistic regression (LR) deployed to on acquired data to manage customer's prediction pattern based on logged energy consumption statistics, states of electrical receptacles, switches and states of immediate environmental condition. The data was acquired departmental lab with two receptacles; one serving an Air Conditioner, other serving a lab desktop Computer and a light point. This data was collected and stored in Google Firebase cloud. The data collected were used to train a Logistic regression model; the model could be deployed to predict the state of acquired energy consumption statistics pattern. A mathematical model for the energy consumption based on the various input parameters was developed as revealed in this paper

2. Theoretical Background

2.1. Machine Learning

Machine Learning was formally defined by Tom Mitchell as a means by which a computer program learns from experience E with respect to some class of Tasks T and performance measure P, if its performance in class T, as measured by P, improves with experience E [11].

According to [18], supervised learning algorithm learn from training of set of data with input features (x) and output feature (y) to generating an hypothesis function (h) as shown in equation 1 (linear regression), features (x) is passed through h revealed predicted variable value (y) as shown in equation 2 (linear regression). Classification algorithm uses the sigmoid function in equation 3 as the predictive function.

$$h_\theta = \theta_0 + \theta_1 x \quad (1)$$

$$y = h_\theta(x) \quad (2)$$

$$y = h_\theta(x) \quad (3)$$

Considering value of θ_0 and θ_1 could be minimize through cost function J (θ_0, θ_1) shown in equation 4.

$$\bar{J}(\theta_0, \theta_1) = \frac{1}{2m}\sum_{i=1}^{m}\left(h_0\left(x^{(i)}\right) - y(i)\right)^2 \tag{4}$$

The study considered gradient descent algorithm to calculate the value of $\theta 0$ and $\theta 1$, this minimizes J ($\theta 0$, $\theta 1$) during convergence operation as revealed equation 4.

$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta j} j(\theta_0, \theta_1) \tag{5}$$

2.2. Internet of Things- Device to Cloud Communication

In March 2015, the Internet Architecture Board (IAB) released a guiding architectural document for networking of smart objects (RFC 7452), which outlines a framework of four common communication models that can be used by IoT devices. Internet of things is the connection of objects that are not necessarily classified as computers to the internet enabling them to send and receive data. Three of these frameworks includes;

1. Device-to-Device Communication through wireless networks such as Bluetooth, Z-wave, ZigBee and the likes.
2. Device to Gateway Model; this involves the connection of this devices to a common gateway that has access to an application service provider or a local server.
3. Device to Cloud Communication; this is the connection of this devices to a cloud service provider for storing data, retrieving data or accessing a defined application. This is the kind of IoT concept that was employed in this project. The Sensor nodes were designed to log the data collected to google firebase cloud via http as shown in figure 1.

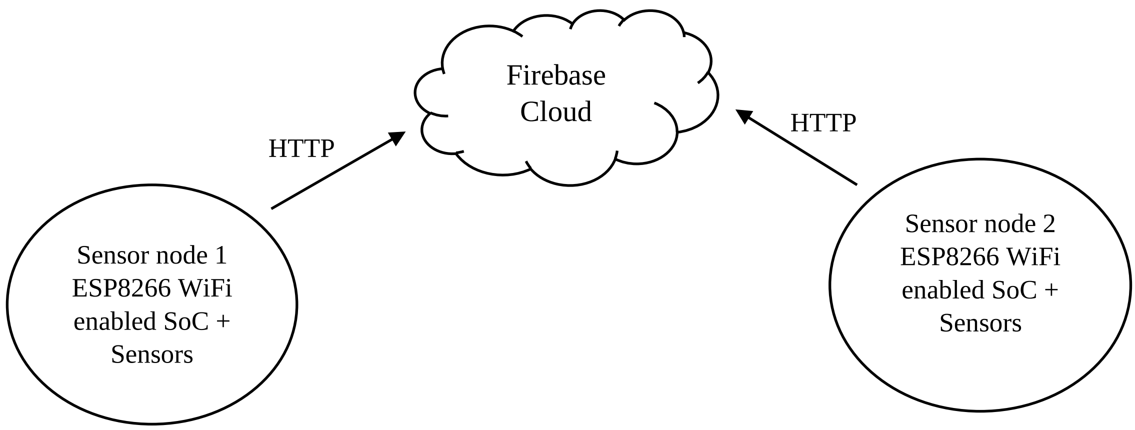

Figure 1. Device to Cloud IoT Model.

3. Research Methodology

To carry out this study, two sockets and a light point in the lab were monitored, including the ambient condition – Light intensity, Humidity, Temperature and also Human presence. As shown in table 1, one socket powers the Air Conditioner; the other socket powers the Lab Computer. A light dependent resistor (LDR) sensor was mounted by the socket to sense the state of socket (on or off). MAX44009, a highly sensitive light sensor, mounted close to the light point helps to sense when the light bulb is On or Off. DHT11 humidity and temperature sensor helps to monitor the temperature and humidity of the Room. Two ESP8266 Node MCUSoC carries a pre-programmed microcontroller (tensilicaX10) and a WiFi module, each serving as the controller for a node.

Table 1. Load Point Monitored and Average Power Rating.

Load	Usage	Average Power (Watt)
Socket 1	Air Conditioner	2800
Socket 2	Desktop Computer	180
Light Point	Lightning	60

3.1. Node A: MAX44009

The sensor (MAX44009) node consists of the following; a 5v switch mode power (SMP) rectified power supply moduled, a system on chip (SOC) ESP8266 Node MCU which carries an esp8266 module, for WiFi communication device and a Tensilica X10 microcontroller. The node includes a DHT11 sensor for measuring temperature and humidity and LDR (socket1) to detect when the socket is switched on or off.

3.2. Node B: Human Motion Detector

Sensor node B consists of PIR motion sensor (human motion detector), a LDR (socket 2), real time monitoring system module (DS1302 RTC), SD_CARD module (data logger), ESP8266 Node MCU SOC and 5v SMP rectified power supply module.

Acquired data through node A are transferred via WiFi to node B logged in SD_CARD module to log the data offline and also connects to the LAB hotspot to send the data to Google Firebase cloud storage, employing the concept of Internet of Things.

3.3. Description of Logged Data

The study acquired data for continuous seven (7) days of the week (DOW), running from Monday to Sunday. The logging hour of the day clocked in 24hours (HD), also featured in minutes, 0-60 (MH) with DS1302 RTC module performing real time clocking function. Considering PIR motion sensor for detection of human presence (HP) as a factor in this study, its output was tagged 1 or 0 for on and off respectively at interval of 2minutes. Another considered in the research was Light Intensity (LI) using MAX44009 sensor in its unit (lux).

Environmental ambient condition was monitored as proposed in the study Temperature (TP); acquired and logged including humidity (HM) using DHT11 sensor. State of Lighting point (LS) was monitored using the MAX44009 light intensity sensor; this was shielded from ambient light in order not to interfere with temperature acquired data.

The state of socket 1and 2 (S1S and S2S) was monitored using LDR to acquired its activities on/off for respective 1 and 0 indicator and the data was logged in every 2 min for 30 days of this study, this concluded the entries to be 11980 (data population) were logged per features. Acquired data was cleaned up addresses error; removing a row with incomplete feature data labeled xx, and ensuring that positive and negative output are within 60% to 40% of the whole data. The cleaning process reduced the data to 10000 per feature.

Approach I: Machine Learning

The machine learning pipeline involves the use of Logistic regression to predict the state of the switches; this is means predicting whether the switch for the load points should be On or Off. It is obvious that this is a classification problem. The sklearn module, the module adopted python script to support system performance. The pipeline followed in the execution of the classification algorithm is shown in Figure 2. The algorithms enhance prediction such as states of the switches and representation of customer's energy consumption pattern. Performance of the model was analyzed by using the Receiver Operating Characteristics (ROC) curve.

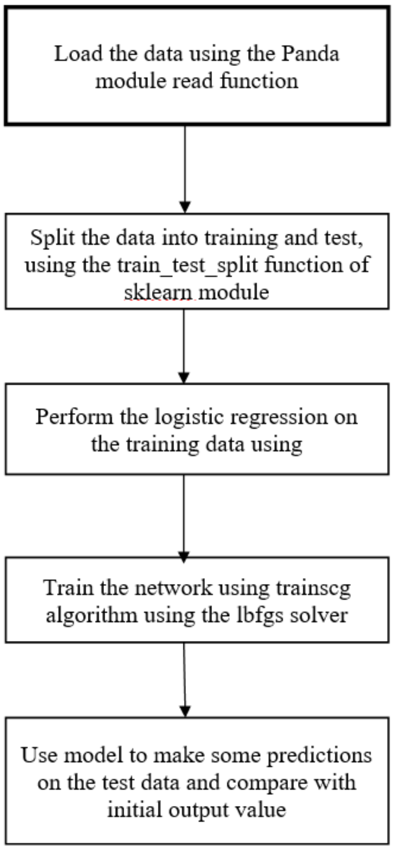

Figure 2. Classification Algorithm.

Approach II: Modeling of Average Power Usage

An alternative approach was taken to describe the energy consumption pattern of the user. From the data collected, electric power usage depends on time, human presence and environmental temperature. The power usage was investigated base on average acquired data; a plot was made and the line of best fit was passed through the data using MATLAB R2017b plot fitting toolbox. The line equation was adopted to model the response such as average power usage for varying values of the temperature, time of the day, or human presence.

4. Results and Discussion

4.1. Result of the Machine Learning Process

4.1.1. Result for Light State Classification Prediction

After training a logistic regression model to classify the state of the light, the performance of the model had properties;

Accuracy: 0.906; log loss: 0.253; AUC (Area Under the ROC curve): 0.971.

Performance of the model was further expressed as ROC (Receiver Operating Characteristic) shown in Figure 3.

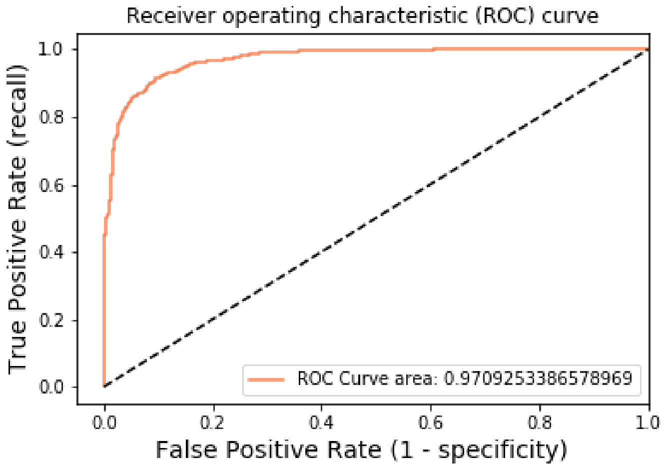

Figure 3. ROC Curve for Light State.

The ROC curve shows the performance of the classification model putting into consideration all the classification thresholds. It has two parameters; TPR on y-axis and FPR on x-axis. The True positive rate is also known as recall and can be expressed as;

$$\text{TPR} = \text{True Positives} / (\text{True Positives} + \text{False Negatives}) \tag{6}$$

The True Positive is the number of tests predicts On (Positive) state for the light, when the actual state is On (Positive). The False Negatives is the number of tests that predicts Off (Negative) state for the light while the actual state is On (Positive). The combination of this as shown in equation 6 gives the True Positive Rate. The True Positive Rate therefore means the probability that an actual positive (On) will be predicted as Positive (On). The False Positive Rate (FPR) can be expressed as;

$$\text{FPR} = \text{False Positives} / (\text{False Positives} + \text{True Negatives}) \tag{7}$$

The False Positive is the number of tests that predicts On (Positive) when the actual state is Off (Negative). The True Negative is the number of tests that predicts Off (negative) when the actual state is Off (Negative). Hence, the False Positive Rate is the probability that an actual Off state (Negative) will be predicted as On (Positive).

4.1.2. Result for Socket 1 State Classification Prediction

After training a logistic regression model to classify the state of the Socket 1, the performance of the model had properties;

Accuracy: 0.851; log loss: 0.349; Area under the ROC curve (AUC): 0.933

The performance of the model was further expressed as Receiver Operating Characteristic (ROC) curve shown in figure 4.

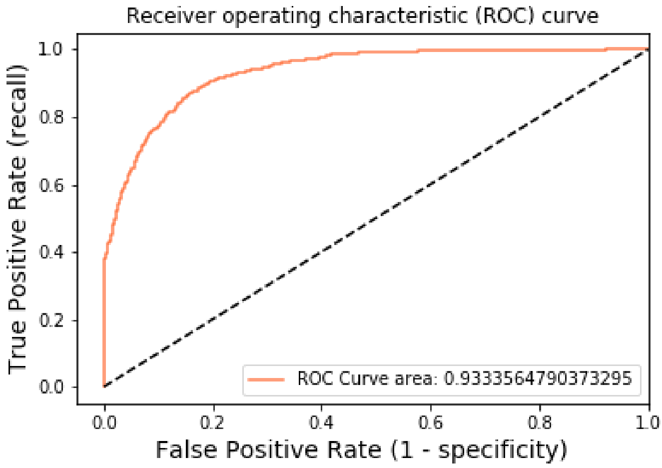

Figure 4. ROC Curve for Socket 1.

The ROC curve shows the performance of the classification model putting into consideration all the classification thresholds. It has two parameters; TPR on y-axis and FPR on x-axis

4.1.3. Result for Socket 2 State Classification Prediction

After training a logistic regression model to classify the state of Socket 2, the performance of the model had properties;

Accuracy: 0.816; Log loss: 0.401; Area under the ROC curve (AUC): 0.902

The performance of the model was further expressed as Receiver Operating Characteristic (ROC) curve shown in figure 5.

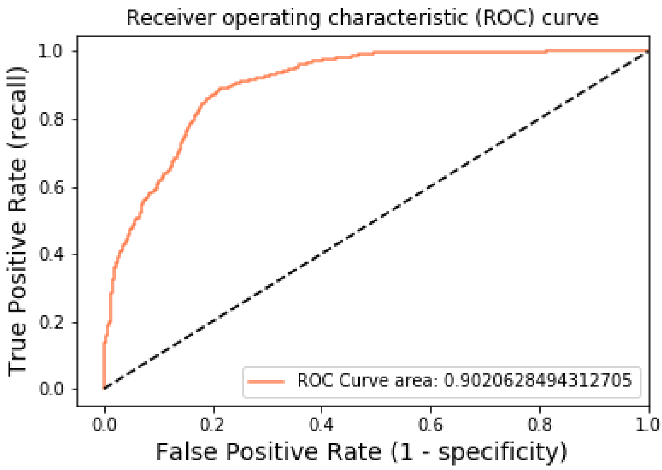

Figure 5. ROC Curve for Socket 2 State.

The ROC curve shows the performance of the classification model putting into consideration all the classification thresholds. It has two parameters; the TPR on y-axis and FPR at x-axis

4.2. Model of Average Power Usage

4.2.1. Effect of Time of the Day on Average Power Usage

Figure 6, revealed a distribution pattern of the study as shown below. A mathematical model of the line of best fit was generated with the aid of the plot fitting tool of MATLAB which relates the hour of the day to average power usage as is shown in equation 8, a polynomial of degree 5 seems more appropriate in fitting the plot.

$$Y = -0.010167X^5 + 0.87074X^4 - 24.699X^3 + 267.23X^2 - 835.17X^1 + 377.36 \quad (8)$$

where,
Y = Average Power Usage in an hour over the number of days when the data was collected.
X = Hour of the day.

It can be observed that maximum peak power usage occurs close to mid-day. The study revealed a steady increase of power usage occurs during working hours; this power usage diminishes during off-peak (not working hour). This plot is accurate since the data was acquired in the laboratory, the opening hours are 8:00am to 16:00pm. Power usage outside this period can be classified as wastage and not consistent with the expectation.

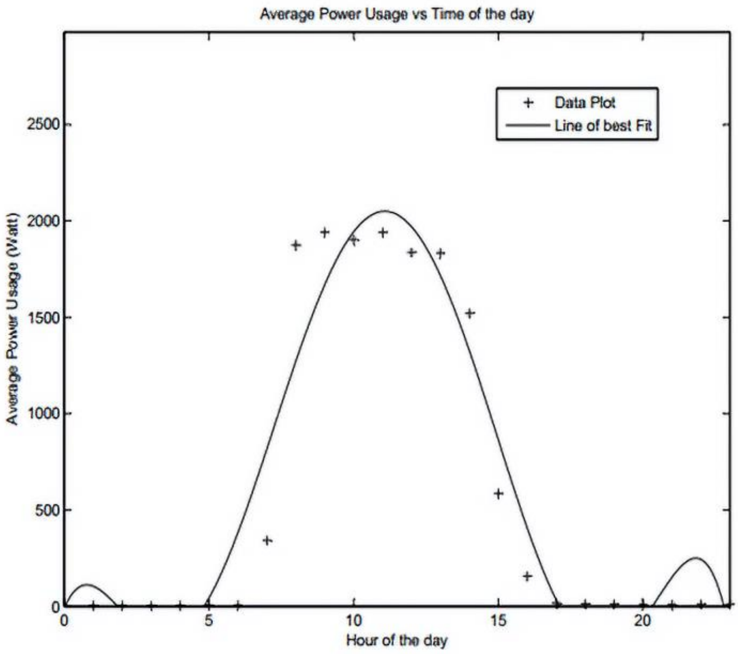

Figure 6. Average Power Usage vs Time of the Day.

4.2.2. Effect of Human Presence on Average Power Usage

Figure 7 shows a plot of human presence rating against average power used. The study model relationship between human presence and its effect on average power usage is shown as equation 9. A polynomial of degree 7 fits the plot for better performance as revealed.

$$Y = -1.4153 \times 10^6 X^7 + 5.1085 \times 10^6 X^6 - 7.491 \times 10^6 X^5 + 5.7023 \times 10^6 X^4 - 2.3724 \times 10^6 X^3 + 5.1067 \times 10^5 X^2 - 44250X^1 + 2858.8 \quad (9)$$

where,
Y = Average Power Usage and X = Human Presence Rating

It was revealed that there is an increase in average power used as human presence rating increases due to energy usage. This means that more people enter the lab region (area), there is a need to make use of appliances such as computer system, phones; thereby switching On socket 2. While Socket 1 could also be switched On to put the Air Conditioner On to cater for the cooling. Technically, when there is no human presence in the lab having the sockets ON and light on can be termed as energy wastage.

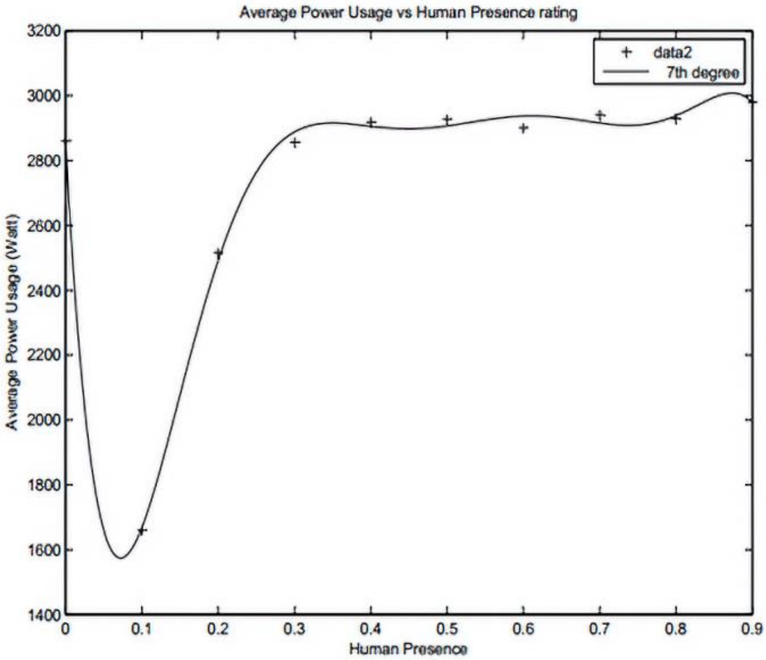

Figure 7. Average Power Usage vs Human Presence Rating.

5. Conclusions

The two approaches adopted in this study were to model and investigated energy consumption pattern. The first approach used involve the training of a Logistic Regression model with input logged data (temperature, humidity, time of the day and human presence rating); the output of the training network was the state of each receptacle treated separately. The logistic regression model was tested with some test data and showed high accuracy in predicting whether the sockets or switch should be on (1) or off (0) based on the input data. The second approach deployed mathematical polynomial equation to model the power consumption of the user based on human presence rating and hour of the day. The study detected peak period of energy usage and automation system could be introduced as On /Off. It was of more interest to be able to detect that a receptacle is On when it is supposed to be Off. Introduction of automation initiative through internet of things (IoTs) applications towards system availability could be supported in this study. Energy prediction can help to minimize wastage of energy by providing inference that can provide feedback to automate switching off receptacles and load points that should be out of use by prediction; this can help to reduce the cost of energy incurred by institutions and estate owners. The load on grid networks and components can also be reduced thereby improving lines against failure and reducing maintenance cost incurred by energy distribution companies. With continuous increase of off-grid power supply to cater for incessant main-grid power supply in developing countries, knowing the consumer’s energy consumption pattern can help to optimize supply of power and improve system availability with minimal supervision. Future study aims design real time data and automation system towards robust intelligent energy consumption monitoring system.

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Declaration of Competing Interest

No conflict of interest was declared by the authors.

Authorship Contribution Statement

Daniel O. Abode: Validation, Design, hardware implementation, Investigation, Writing- Original draft preparation, Data analysis.
Omowumi G. Olasunkanmi: Validation, Visualization, Formula Analysis, Writing- Reviewing and Editing.
Waliu O. Apena: Software, Data curation, Resources, Final correction and Editing
Samson A. Oyetunji: Conceptualization ideas, Supervision, Methodology

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