Estimation of Unregulated Energy in Office Buildings Using Fuzzy Inference System

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Abstract - *A fuzzy inference system-based technique that estimates the energy consumed by unregulated energy loads (UELs) in operational office buildings is presented. The technique employs IF-THEN rules that were developed using field data collected from case study offices. The field data were collected using smart energy monitoring devices that were installed at the case study offices. The inputs required by the technique are power ratings of UELs and consumption factors. The consumption factors are determined through the administration of questionnaires to the users of the UELs. The technique fuzzifies the consumption factors, applies inferences, and defuzzifies the outputs of the inferences to yield UEL energy consumed. The method was tested on data collected from the case study offices and was found to be effective.*

Key Words: Building, Energy, Fuzzy inference system, Unregulated energy, Unregulated load.

1. INTRODUCTION

The need to reduce global electricity consumption, particularly from fossil fuel-based energy sources have heightened in recent times due to concerns about increasing greenhouse gas emission. As a result, attention is being paid to sectors that hold significant energy saving potentials to cut down on energy consumption, in addition to exploring environmentally friendly energy sources such as solar energy. Buildings have been identified as significant energy consumers that hold significant energy saving potentials. Buildings are estimated to consume about 40% of the world's electric energy [1]. Therefore, much attention has been focused on finding potential areas for reducing energy consumption in buildings [3-6]. To this end, researchers and energy modelers are working to develop appropriate tools to enable the analysis of building energy consumption to aid the formulation of cost-effective energy saving measures to optimize energy utilization.

Building loads can be categorized into regulated energy loads (RELs) and unregulated energy loads (UELs). Regulated loads are heating, ventilation, and air-conditioning (HVACs) loads as well as lighting loads. Unregulated loads include computers, servers, printers, scanners, and photocopiers. Building energy estimation has been skewed towards regulated loads. This is because regulated loads are considered as major energy end-use equipment. Therefore, design approaches have largely focused on them. However, UELs (also known as plug loads, miscellaneous energy loads and small power equipment loads) account for about 30% of a buildings' energy consumption [3]. This percentage could be as high as 50% for energy efficient buildings [3]. Furthermore, UELs have been projected to increase by 7.1% annually as compared to a 1% annual rise in regulated loads [6]. Therefore, it is essential to include UELs in the energy consumption analysis of buildings.

Attempts to include UELs in building energy analysis have relied on plug load energy benchmarks, equipment nameplate ratings and standard operational hours [7-13] since device level monitoring is cumbersome and expensive. However, these approaches do not give accurate reflections of actual energy consumptions. For example, the use of power profiles and operating hours provided in the 2nd and 3rd editions of the Charted Institute of Building Services Engineers (CIBSE) guide F [12, 13] results in overestimation of energy usage [7]. Consequently, other methods have been proposed in literature to overcome the shortfalls of the CIBSE guide F. These methods employ non-invasive load monitoring techniques and prediction models. However, these methods have significant deficiencies.

Non-intrusive load monitoring techniques such as the methods in [14-16] require branch circuit and complex algorithms to learn signature patterns for unregulated energy usage prediction. Furthermore, non-intrusive techniques are expensive to install and may interpret power system disturbance signatures as plug load signatures [17]. Prediction models such as those presented in [18, 19] require users to produce occupancy count of office spaces to enable the estimation of unregulated energy usage. However, occupancy count of offices alone is not enough to produce accurate energy predictions. Besides, the determination of accurate occupancy counts requires the deployment of occupancy sensors which is time consuming and costly. It follows from the above that existing approaches for estimating unregulated energy are either cumbersome, complex, expensive to implement or have significant errors. Therefore, there is the need to develop techniques to overcome these deficiencies.

This work addresses this need. It presents a fuzzy inference system-based technique to estimate the energy consumed by UELs in operational office buildings. The proposed technique uses IF-THEN rules that were constructed from an analysis of field data collected from some case study offices. The data analysis was aided by fuzzy c-means clustering. To use the technique, a UEL energy estimator must obtain the power rating of the UEL whose energy consumption is to be determined. The estimator then proceeds to administer a questionnaire to the user of the UEL to produce data on four UEL consumption factors (CFs). The four consumption factors are usage factor (UF), active mode factor (AF), idle mode factor (IF) and off mode factor (OF). The estimator then feeds the data into the developed fuzzy inference system which fuzzifies the consumption factors, apply inferences, and defuzzifies the outputs of the inferences to yield the energy consumed. The defuzzification process feeds on energy ranges derived from the data on UEL power rating and usage factor (UF). The proposed technique offers several advantages including simple implementation, the non-requirement of measurement instruments and occupancy sensing devices, low cost of implementation and low margins of error.

The remaining sections of the paper are organized as follows: Sections 2 and 3 explain the fuzzy inference system (FIS) and fuzzy c-means clustering, respectively. Section 4 presents a methodology used to characterize the energy usage of UELs. Section 5 explains the approach used to collect field data for rules development as well as how the fuzzy c-means was employed for analysis of collected data to aid rules development. Section 6 describes the modelling of the fuzzy inference system. In Section 7, the proposed technique for UEL energy estimation is presented. The approach to generate another set of data to test the proposed technique is presented in Section 8. The test results and analysis of same are presented in Section 9. Conclusions drawn are presented in section 10.

2. FUZZY INFERENCE SYSTEM

Fuzzy inference system (FIS) or fuzzy logic is a soft computing method that has been widely used to solve various problems, including energy related problems. It consists of three layers namely, input layer, inference layer and output layer. These layers execute three tasks namely, fuzzification, inferences and defuzzification [20]. During the fuzzification process, a crisp input set is fuzzified using a fuzzifier that uses membership functions to get a fuzzy set. Examples of used membership functions are triangular, trapezoidal and gaussian [20]. The fuzzy set runs through an inference system which has basic IF-THEN rules that map the input fuzzy set to an output fuzzy set. The fuzzy IF-THEN rules are a collection of linguistic statements that describe how a system should make decisions regarding classifying an input or controlling an output. The output fuzzy set is then deffuzified using a deffuzifier to get a crisp output. Examples of deffuzifiers are center of gravity and center of sums.

For a triangular membership function such as shown in Fig - 1, the degree of membership, $U(x)$, for a crisp input, x, can be obtained using (1) [20].

$$U(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{k-a}, & a < x \le k \\ \dfrac{b-x}{b-k}, & k < x < b \\ 0, & x > b \end{cases} \tag{1}$$

where x is a crisp input and a, k and b are the lower limits, average value and upper limits respectively.

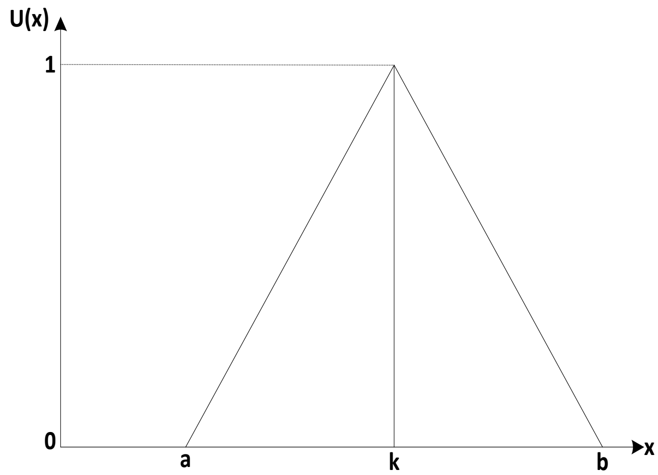

Fig. -1. Triangular membership function

For an output fuzzy set with a triangular membership function such as is shown in Fig -2, the defuzzified value, x^*, is obtained by the center of gravity defuzzification method (the method employed in the proposed technique) using Eqn. (2)[20].

$$x^* = \frac{\sum_{i=1}^{N} A_i \bar{x}_i}{\sum_{i=1}^{N} A_i} \tag{2}$$

where N indicates the number of sub-areas, A_i and $\bar{x}$ represents the area and centroid of area respectively, of the i^{th} sub-area.

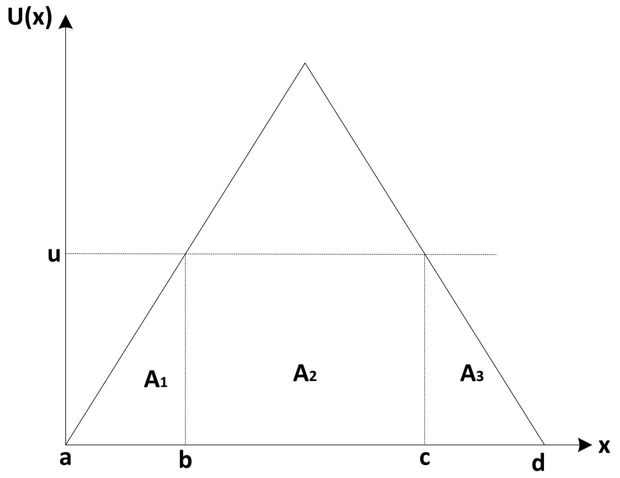

Fig. -2. Triangular function for defuzzification

3. FUZZY C-MEANS

Fuzzy c-means (FCM) is a commonly used soft computing clustering technique [21-23]. It divides a finite dataset *X* into *c* clusters. Given a d-dimensional data, X, the fuzzy partitioning is performed subject to the iterative minimization of an objective function. Given that [23],

1. $X = \{x_1, x_2, \ldots, x_n\}$ is a finite dataset, where $x_i = \{x_{i1}, x_{i2}, \ldots, x_{ij}\}$ is a d-dimensional object and x_{ij} is the j^{th} property of the i^{th} object,
2. $C = \{C_1, C_2, \ldots, C_c\}$ denotes the c clusters to be formed,
3. $V = \{V_1, V_2, \ldots, V_c\}$ represents the c d-dimensional cluster centroids, and
4. $U = (u_{ik})_{(n \times c)}$ is a fuzzy partition matrix, and u_{ik} is the degree of membership of the i^{th} object in the k^{th} cluster, where $\sum_{k=1}^{c} u_{ik} = 1, \forall i = 1, \ldots, n$.

The objective function for the clustering is the quadratic sum of weighed distances from the samples to the cluster centroid in each cluster and is given by eqn. (3) [23].

$$J_i(U,V) = \sum_{k=1}^{c}\sum_{i=1}^{n} u_{ik}{}^{m} d_{ik}{}^{2} \tag{3}$$

Where d_{ik} is the euclidean distance between the ith object and the kth cluster centroid and m is a fuzziness index which controls the fuzziness of the memberships.

The fuzzy c-means clustering was used to help in understanding the collected field data to develop the IF-THEN rules employed by the proposed technique for UEL energy estimation. However, the implementation of the finalized technique will not require the use of fuzzy c-means clustering.

4. CHARACTERIZATION OF THE ENERGY CONSUMPTION OF UELS

To enable accurate energy estimation, a thorough characterization of the energy consumption of UELs is required. A previous work in [24] has shown that the energy consumed by UELs can be determined using the optimum energy for three usage modes namely, active mode, idle mode and off mode. For the case study offices in [24], optimum energy in the three modes for the various devices were established by determining optimum power drawn in each of the three modes as well as the associated optimum usage periods. This work proposes the use of optimum factors for power drawn in each mode, as an extension to the work in [24]. The proposed optimum factors will enable the determination of the optimum power drawn by devices of the same kind as those studied in [24] but whose power ratings are different. For example, whereas the laptop studied in [24] has a rating of 140W, other laptops whose energy consumption must be determine may have different power ratings. If P_{nk} is the optimal power drawn by device n of power rating, P_n, in operational mode k (where k is either 1, 2 or 3 and denotes active, idle and off modes respectively), then the proposed optimum factor for device n in operation mode k, ρ_{nk}, is obtained using (4).

$$\rho_{nk} = \frac{P_{nk}}{P_n} \tag{4}$$

where $n = 1, 2, 3, \ldots, N$ and $k = 1, 2, 3$.

With the determination of these optimum factors, the optimum power drawn by a UEL of the same kind as that studied in [24] but whose power rating is different from that studied in [24], can be determined. Given a new UEL, n_x, where x is a variance (i.e., having a different power rating) of device n studied in [24], with power rating P_{n_x}, the optimum power drawn in the various modes, $P_{n_x k}$, is determined using (5).

$$P_{n_x k} = \rho_{nk} \times P_{n_x} \tag{5}$$

Further to the three optimum usage periods (i.e, optimum active mode usage period, optimum idle mode usage period, and optimum off mode usage period) proposed in [24], this work proposes that the operating period of a UEL in each of the three power modes can be further categorized into three sub-usage periods. The sub-usage periods are low operating period, medium operating period, and high operating period. For example, a UEL drawing power in active mode may do so over a low operating period, medium operating period, or a high operating period. Consequently, the energy consumed by a UEL in each of the three operational modes can also be categorized into low energy, medium energy, and high energy. Thus, the low energy, $E_{n_x kl}$, consumed by device n_x in mode k is given by (6). The medium energy, $E_{n_x km}$, consumed by device n_x in mode k is given by (7). The high energy, $E_{n_x kh}$, consumed by device n_x in mode k is given by (8).

$$E_{n_x kl} = P_{n_x k} \times T_{n_x kl} \tag{6}$$

$$E_{n_x km} = P_{n_x k} \times T_{n_x km} \tag{7}$$

$$E_{n_x kh} = P_{n_x k} \times T_{n_x kh} \tag{8}$$

Where $P_{n_x k}$ is the optimum power drawn by device n_x in operational mode k, $T_{n_x kl}$ is the low usage period of device n_x in operational mode k, $T_{n_x km}$ is the medium usage period of device n_x in operational mode k and $T_{n_x kh}$ is the high usage period of device n_x in operational mode k.

5. DATA GENERATION AND CLUSTERING FOR IF-THEN RULES DEVELOPMENT

To generate data and analyze them to develop the IF-THEN rules, smart energy measurement devices were installed in case study offices to monitor the energy consumed by UELs. The fuzzy c-means clustering was then employed for data analysis to enable the development of the rules. The sub-sections that follow explain how the field measurements were done to generate the data and how the fuzzy c-means clustering was employed for data analysis to support rules development.

5.1 Field measurement of energy consumption by UELs

Data were collected from seven offices in the Levine building at the College of Engineering of the Kwame Nkrumah University of Science and Technology, Kumasi. The collection of data was done for a period of twelve weeks. The building is a one-storey facility. Five of the offices monitored were on the first floor while the other two were on the ground floor. The offices on the first floor were (a) two offices of the Department of Civil Engineering comprising an office for the Administrative Assistant and that for the Head of Department (HoD), (b) two offices of the Department of Geological Engineering also comprising an office for the Administrative Assistant and that for the HoD, and (c) one office for the Administrative Assistant of the Department of Geomatic Engineering. The two offices on the ground floor (i.e., LB33 and LB36) were the offices occupied by two lecturers of the Department of Civil Engineering.

Regarding the office for the Administrative Assistant of the Department of Civil Engineering, the UELs monitored were one desktop computer, one laptop computer, one printer, and one photocopier. For the HoD's office of this Department, the UEL monitored was one laptop. The UELs monitored at the office for the Administrative Assistant of the Department of Geological Engineering were one desktop computer, one printer and one photocopier while for the HoD's office, the UEL monitored was one laptop computer. With regards to the office of the Administrative Assistant of the Department of Geomatic Engineering, the UELs monitored were one desktop computer and one printer. The UELs monitored at LB33 were one desktop computer, one laptop computer and one printer while those monitored at LB36 were one desktop computer and one laptop computer. The number of UELs selected for monitoring was based on the availability of smart devices.

For each office, smart energy monitoring devices were installed. The smart energy devices were smart plug monitor adaptors [25], smart motion sensors [26], and a gateway [27]. The smart plug monitor adapters were connected to the sockets and the UELs plugged into them for their energy usage to be monitored. The smart adapters captured the power drawn by connected devices, every 10 seconds. The smart motion sensors enabled the capture of occupancy information. The gateway enabled the sending of occupancy and energy data to a server. Fig -3 is an image that shows two smart plug monitor adaptors fitted in sockets, with the plugs of two UELs connected to them. Fig -4 also shows a gateway and a modem used for sending collected energy data to a server.

Fig – 3. Smart plug monitor adaptors with fitted plugs of UELs

Fig -4. Gatway and moderm

5.2 **Fuzzy c-means clustering**

For each UEL, data for the measured power drawn were categorized into data sets for active mode power, idle mode power and off mode power. The categorization was done by applying the fuzzy c-means clustering algorithm to the data on power drawn, associated and usage periods. Based on the categorization of the power drawn, the associated ranges of usage periods for the various modes were also categorized into active mode periods, idle mode periods and off mode periods. For each category of usage periods, the fuzzy c-means clustering technique was used to further classify it into minimum period, medium period, and maximum period. The flowchart for the data clustering is shown as Fig -5. The clustering process is further outlined in six steps as follows:

Step 1: Data preprocessing: This involves the cleaning and normalization of each data point.
Step 2: Initialization of the number of clusters, *c*, and fuzziness index, *m*. For this work, *c* was assigned a value of *3* for each mode to classify data into minimum period, medium period, and maximum period. The fitness index was set to 2.
Step 3: Assign degree of membership for each data point in each cluster.
Step 4: Update the cluster centers.
Step 5: Update the degree of membership.
Step 6: Check stopping criterion. If yes, display clusters, otherwise, go to step 4.

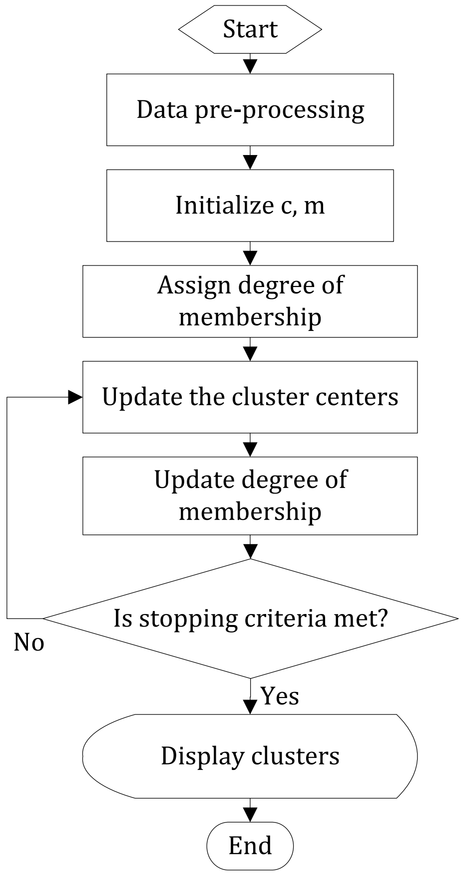

Fig -5. Fuzzy C means clustering of usage data.

6. MODELLING OF PROPOSED FUZZY INFERENCE SYSTEM APPROACH

The fuzzy inference system for UEL energy estimation was modelled in MATLAB. It had four inputs and three outputs. Fig -6 shows a snapshot of the four input variables and three output variables of the FIS for one of the studied UELs (i.e., desktop computer).

The four inputs related to four consumption factors. These were usage factor (UF), active mode factor (AF), idle mode factor (IF) and off mode factor (OF). These factors were arrived at as a means of characterizing the usage of UELs as explained in Section 4. The UF for a UEL provides information about the extent to which it is used. The AF gives the extent to which a UEL is operated in active mode. The IF provides the extent to which a UEL is operated in idle mode. The OF indicates the extent to a UEL is left in off mode. Each input (UF, AF, IF and OF) had five membership functions. The membership functions were always, often, sometimes, rarely and never. Fig -7 shows the triangular membership functions for one of the four input variables (i.e., UF). The triangular membership function was chosen for the input variables because of its simplicity. The other factors (AF, IF and OF) had the same triangular membership function. The triangular membership function parameters (ranges and overlaps) were tuned to meet the trends established from the analysis of the energy consumption data collected in the field measurements as explained in Section 5.

The three output variables were active usage, idle usage (or low active usage), and off usage. Each of the three output variables had three linguistic variables namely, low consumption, medium consumption and high consumption. Fig -8 shows the output membership function for the active usage of a 160W desktop computer. Here too, the triangular membership function was used. The other studied UELs had similar membership functions. The limits of each output triangular membership function were also set guided by the trends in the empirical data.

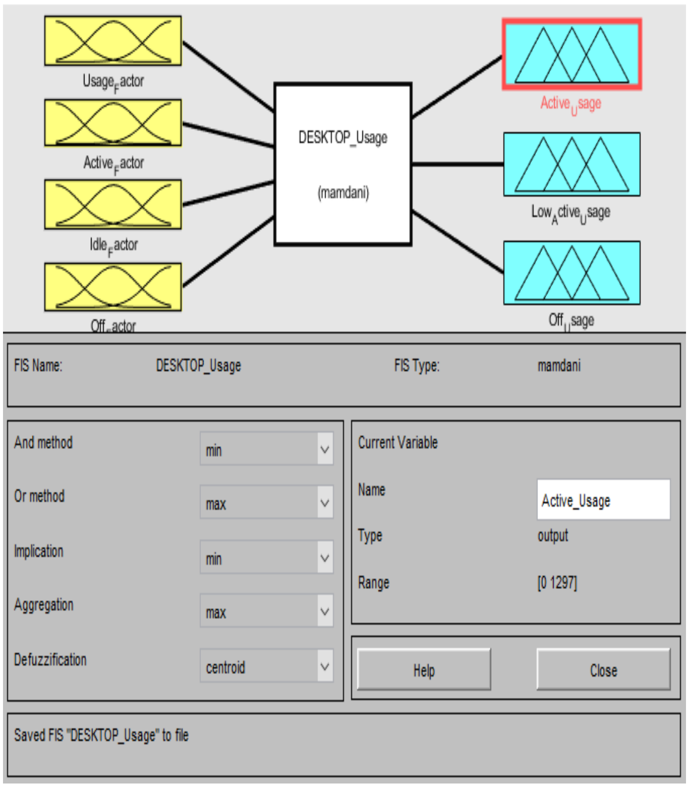

Fig -6. Input and Output variables for a desktop computer.

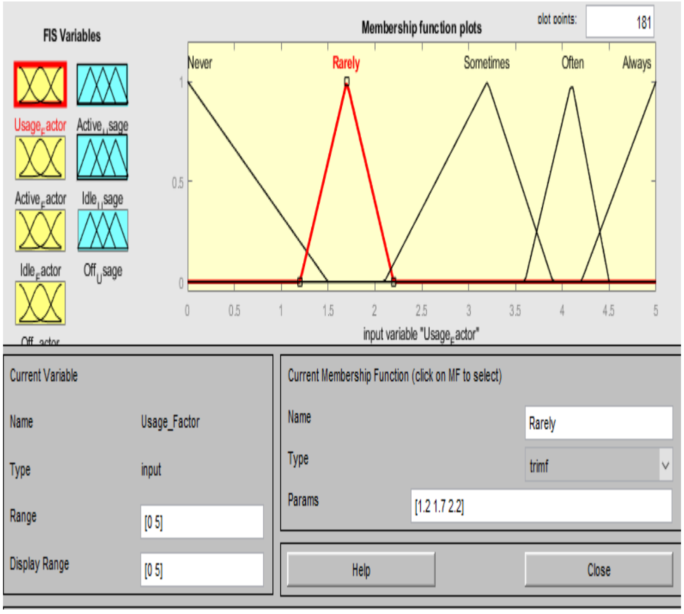

Fig -7. Usage factor membership function.

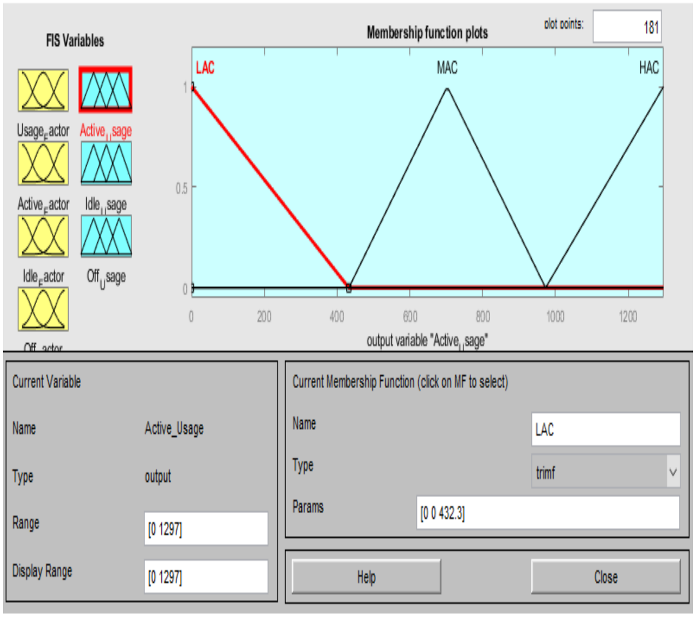

Fig -8. Active usage membership function for Desktop computer of rating 160W

At the inference stage, seventy-five different rules were constructed. These rules were developed using experts' knowledge and the gathered energy consumption data. For each UEL, to determine energy consumption in active mode, the input variables UF and AF are used. For idle or low active energy consumption, UF and IF are used. Regarding off mode energy consumption, UF and OF are used. The rules are as shown in Tables 1, 2 and 3. All the rules had equal weights.

Table -1. Fuzzy rules relating to active mode factors and usage factors.

AF \ UF	Never	Rarely	Sometimes	Often	Always
Never	LAC	LAC	LAC	LAC	LAC
Rarely	LAC	MAC	MAC	MAC	MAC
Sometimes	LAC	MAC	MAC	HAC	HAC
Often	LAC	MAC	HAC	HAC	HAC
Always	LAC	MAC	HAC	HAC	HAC

Table -2. Fuzzy rules relating to idle mode factors and usage factors.

IF \ UF	Never	Rarely	Sometimes	Often	Always
Never	LIC	LIC	LIC	LIC	LIC
Rarely	LIC	MIC	MIC	MIC	MIC
Sometimes	LIC	MIC	MIC	HIC	HIC
Often	LIC	MIC	HIC	HIC	HIC
Always	LIC	MIC	HIC	HIC	HIC

Table -3. Fuzzy rules relating to off mode factors and usage factors.

OF \ UF	Never	Rarely	Sometimes	Often	Always
Never	LOC	LOC	LOC	LOC	LOC
Rarely	LOC	MOC	MOC	MOC	MOC
Sometimes	LOC	MOC	MOC	HOC	HOC
Often	LOC	MOC	HOC	HOC	HOC
Always	LOC	M0C	HOC	HOC	HOC

The abbreviations in Tables 1, 2 and 3 are defined as follows:
LAC - low active mode consumption
MAC - medium active mode consumption
HAC - high active mode consumption
LIC - low idle mode consumption
MIC - medium idle mode consumption
HIC - high idle mode consumption
LOC - low off mode consumption
MOC - medium off mode consumption
HOC - high off mode consumption

7. PROPOSED TECHNIQUE FOR ESTIMATING THE ENERGY CONSUMPTION OF UELS

Fig -9 shows a flowchart of the proposed method. The operational procedure of the technique is further outlined as follows:

Stage 1: *Input device type and power rating* – The estimator inputs the type of UEL (such as desktop computer, laptop, printer, or photocopier) whose energy estimate is to be obtained and proceeds to input the nameplate wattage of the UEL.

Stage 2: *Input device usage data* – The usage data required for the UEL are in the form of four consumption factors. The consumption factors are usage factor (UF), active mode factor (AF), idle mode factor (IF) and off mode factor (OF). The consumption factors are determined from specific responses that will be provided by UEL users, to a set of questions. The questions relate to how often the UEL is (a) used; (b) operated in active mode, (c) kept in idle mode and (d) left in off mode. The required specific responses to yield the consumption factors are: always, often, sometimes, rarely or never. Responses to the questions to (a), (b), (c) and (d) produce the factors UF, AF, IF and OF respectively.

Stage 3: Fuzzify consumption factors – Here, the consumption factors UF, AF, IF and OF which are linguistic variables (i.e., always, often, sometimes, rarely, or never) are assigned crisp numerical values and matched to a degree of membership to obtain an input fuzzy set. The input fuzzy set has values that range from 0 to 1. The matching is done using a triangular membership function.

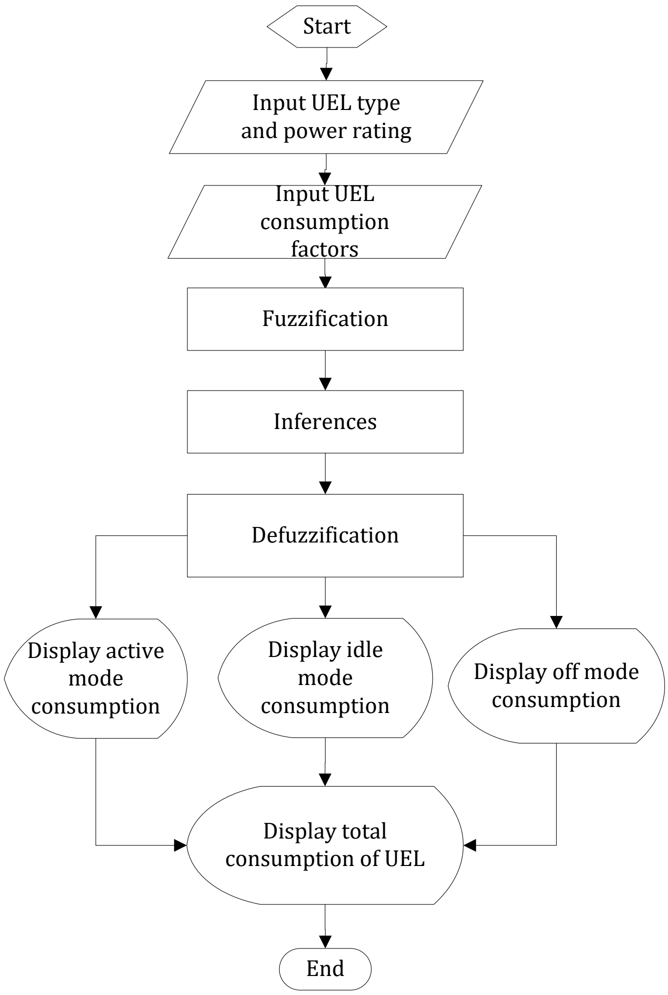

Fig -9. Flowchart for proposed technique.

Stage 4: Apply inferences: During the inference stage, a set of linguistic statements that describe how the system should make a decision regarding classifying the input or controlling the output variable is applied. Depending on the input, a corresponding rule will be inferred. Here, seventy-five different rules are used. The rules are as shown in Tables 1, 2 and 3.

Stage 5: Defuzzify inference results: Here, the fuzzy inference results are converted into crisp outputs. In this work, the center of gravity (COG) method of defuzzification is used. The equation associated with this method has been presented in Section 2 above as (2).

Stage 6: Display energy consumptions: The energy consumed by the UEL in the active, idle and off modes are displayed as well as the total energy consumed by the UEL. The total energy is the sum of the energy consumed in the various modes. The displayed values represent weekly energy consumptions.

8. GENERATION OF CONSUMPTION FACTORS FOR TESTING OF PROPOSED METHOD

To generate consumption factors (UF, AF, IF and OF) to evaluate the performance of the proposed technique, a questionnaire was developed to collect input data from users of the UELs at the case study offices. For each UEL, the user provided responses to the following questions:

(a) How frequently is the UEL used?
(b) To what extent is the UEL put into active usage?
(c) To what extent is the UEL operated in the idle mode?
(d) To what extent is the UEL shut down, but not switched off at the socket?

The questions were clearly explained to the users to enable them provide accurate responses. For each question, the user was required to select one of the following responses: always, often, sometimes, rarely, or never. Responses to the questions (a), (b), (c) and (d) produced the consumption factors UF, AF, IF and OF respectively. Questionnaires were administered to occupants of the case study offices.

9. RESULTS AN ANALYSIS

Results are presented and analyzed under 3 headings namely, ranges of energy consumption for monitored UELs, sample energy estimation for UELs, and comparison of energy estimates with measured data.

9.1 Ranges of energy consumption for monitored UELs

Table 4 shows the optimum factors in the three modes for the UELs studied in this work. These optimum factors were computed using (4). The optimum factors were determined by extracting the wattages of the UELs studied in [24] and the associated reported optimum power drawn in the various modes [24]. For example, for the laptop computer that was studied in [24] which had a power rating of 140W, and reported optimum power drawn in active mode of 26.17W, the optimum factor in active mode, determined using (4), is 0.187. Consequently, the generalized optimum power drawn by variances of the studied UELs, in the three modes, computed using (5) is shown in Table 5. Table 6 provides the ranges of measured and classified (using fuzzy

Table -4. Optimum factors for studied UELs.

UEL	Optimum factor in active mode	Optimum factor in idle mode	Optimum factor in off mode
Desk. Comp.	0.284	0.087	0.038
Laptop	0.187	0.094	0.025
Printer	0.490	0.093	0.007
Photocopier	0.656	0.025	0.005

Table -5. Optimum power drawn for energy estimation.

UEL	Optimum power drawn in active mode	Optimum power drawn in idle mode	Optimum power drawn in off mode
Desk. Comp.	$0.284P_{n_x}$	$0.087P_{n_x}$	$0.038P_{n_x}$
Laptop	$0.187P_{n_x}$	$0.094P_{n_x}$	$0.025P_{n_x}$
Printer	$0.490P_{n_x}$	$0.093P_{n_x}$	$0.007P_{n_x}$
Photocopier	$0.656P_{n_x}$	$0.025P_{n_x}$	$0.005P_{n_x}$

Table -6. Ranges of usage duration in hours

UEL	Active mode	Idle mode	Off mode
Desktop Computer			
Minimum duration	0 - 9.51	0 - 12.29	0 - 3.73
Medium duration	9.51 - 21.41	12.29 - 24.58	3.73 - 7.46
Maximum duration	21.41 - 28.54	24.58 - 34.41	7.46 - 11.18
Laptop			
Minimum duration	0 - 12.57	0 - 4.21	0 - 4.29
Medium duration	12.57 - 28.83	4.21 - 8.79	4.29 – 9.90
Maximum duration	28.33 - 37.93	8.79 - 11.78	9.90 – 14.86
Printer			
Minimum duration	0 - 1.28	0 - 1.61	0 – 19.17
Medium duration	1.28 – 2.94	1.61 - 3.39	19.17 – 43.28
Maximum duration	2.94 – 3.86	3.39 – 4.54	43.28 – 64.9
Photocopier			
Minimum duration	0 - 0.78	0 – 5.30	0 – 33.77
Medium duration	0.78 – 1.56	5.30 – 11.16	33.77 – 68.28
Maximum duration	1.56- 2.19	11.16 – 14.95	68.28 – 117.85

c-means) usage durations (i.e., ranges for $T_{n_x kl}$, $T_{n_x km}$ and $T_{n_x kh}$) for the three modes. Table 7 presents the ranges of energy consumed, in line with (6), (7) and (8).

Table -7. Ranges of energy consumption in watt-hours

	Active mode	Idle mode	Off mode
	Desktop Computer		
LC range	$0-2.70P_{n_x}$	$0-1.07P_{n_x}$	$0-0.14P_{n_x}$
MC range	$2.70P_{n_x}-6.08P_{n_x}$	$1.07P_{n_x}-2.14P_{n_x}$	$0.14P_{n_x}-0.28P_{n_x}$
HC range	$6.08P_{n_x}-8.11P_{n_x}$	$2.14P_{n_x}-2.99P_{n_x}$	$0.28P_{n_x}-0.42P_{n_x}$
	Laptop		
LC range	$0-2.35P_{n_x}$	$0-0.40P_{n_x}$	$0-0.11P_{n_x}$
MC range	$2.35P_{n_x}-5.39P_{n_x}$	$0.40P_{n_x}-0.83P_{n_x}$	$0.11P_{n_x}-0.25P_{n_x}$
HC range	$5.39P_{n_x}-7.09P_{n_x}$	$0.83P_{n_x}-1.11P_{n_x}$	$0.25P_{n_x}-0.37P_{n_x}$
	Printer		
LC range	$0-0.63P_{n_x}$	$0-2.0P_{n_x}$	$0-0.13P_{n_x}$
MC range	$0.63P_{n_x}-1.44P_{n_x}$	$2.0P_{n_x}-3.15P_{n_x}$	$0.13P_{n_x}-0.30P_{n_x}$
HC range	$1.44P_{n_x}-1.89P_{n_x}$	$3.15P_{n_x}-4.22P_{n_x}$	$0.30P_{n_x}-0.43P_{n_x}$
	Photocopier		
LC range	$0-0.51P_{n_x}$	$0-0.13P_{n_x}$	$0-0.17P_{n_x}$
MC range	$0.51P_{n_x}-1.02P_{n_x}$	$0.13P_{n_x}-0.28P_{n_x}$	$0.17P_{n_x}-0.34P_{n_x}$
HC range	$1.02P_{n_x}-1.44P_{n_x}$	$0.28P_{n_x}-0.37P_{n_x}$	$0.34P_{n_x}-0.59P_{n_x}$

The abbreviations in Table -7 are defined as follows:
LC – Low consumption
MC – Medium consumption
HC – High consumption

9.2 Sample energy estimation for studied UELs

A sample energy estimation, by hand, is presented to demonstrate the working of the proposed method. The estimation is done in line with stages 1 – 6 of the proposed method, explained in Section 7. The sample estimation is in relation to the energy consumption of the monitored desktop computer at the office for the Administrative Assistant of the Department of Civil Engineering. The estimation as per the various stages are presented as follows:

Stage 1: The device type was recorded as desktop computer and the power rating obtained from the name plate was 160W.

Stage 2: The administrative assistant provided responses to the questionnaire on usage data to the effect that the usage factor (UF) for the device was "often", active factor (AF) was "rarely", idle factor (IF) was "often" and off factor (OF) was "rarely". These factors were so because per the administrative assistant, the computer is switched on the moment the office opens and only turned off at the socket when work closes, and that it is barely used for processing documents. Rather, a laptop at the office is mostly used for processing documents.

Stage 3: The crisp inputs for the consumption factors UF, AF, IF and OF were 4, 2, 4 and 2, respectively. The corresponding degree of membership that gives the input fuzzy set, using the triangular member function together with (1), are determined as follows:

$$U_{UF}(x=4, a=3.6, k=4.1) = \frac{4-3.6}{4.1-3.6} = 0.8$$

$$U_{AF}(x=4, b=2.2, k=1.7) = \frac{2.2-2}{4.1-1.7} = 0.4$$

$$U_{IF}(x=4, a=3.6, k=4.1) = \frac{4-3.6}{4.1-3.6} = 0.8$$

$$U_{OF}(x=4, b=2.2, k=1.7) = \frac{2.2-2}{4.1-1.7} = 0.4$$

Furthermore, the output fuzzy sets based on the inferences are obtained as follows:

(a). Fuzzy output set for active Mode
$$= \min(U_{UF}, U_{AF}) = \min(0.8, 0.4) = 0.4$$

(b). Fuzzy output set for idle mode
$$= \min(U_{UF}, U_{IF}) = \min(0.8, 0.8) = 0.8$$

(c). *Fuzzy output set for off mode*
$$= \min(U_{UF}, U_{OF}) = \min(0.8, 0.4) = 0.4$$

Stage 4: For the determination of active, idle and off energy consumption, reference is made to Tables 1, 2 and 3 respectively. From Table 1, with UF being "often" and AF being "rarely" the consumption is inferred to be medium active consumption (MAC). From Table 2, with UF being "often" and IF being "often", the consumption is inferred to be high idle consumption (HIC). Lastly, from Table 3, with UF being "often" and OF being "rarely", the consumption is inferred to be medium off consumption (MOC). Therefore, from Table 7, the ranges of energy consumed by the desktop computer (with $P_{n_x} = 160$) are as follows:

(a). Range of energy consumed in active mode (i.e., MAC) is $(2.70P_{n_x} - 6.08P_{n_x})$ which gives a range of $(432.0 - 972.8)$.

(b). Range of energy consumed in idle mode (i.e., HIC) is $(2.14P_{n_x} - 2.99P_{n_x})$ which gives a range of $(342.4 - 478.4)$.

(c). Range of energy consumed in off mode consumption (i.e., MOC) is $(0.14P_{n_x} - 0.28P_{n_x})$ which gives a range of $(22.4 - 44.8)$.

Stage 5: Using the center of gravity (COG) method of defuzzification, the triangle for evaluating the active mode energy consumption is constructed as shown in Fig -10, using the ranges of power drawn in MAC (i.e., $(432.0 - 972.8)$ and the fuzzy output set for active mode of 0.4. Consequently, defuzzification is done as follows using Eqn. 2:

$$A_1 = \frac{1}{2} \times (540.4 - 432.0) \times 0.4 = 21.68$$

$$\bar{x}_1 = \frac{432.0 + 540.4 + 540.4}{3} = 504.27$$

$$A_2 = (849.2 - 540.4) \times 0.4 = 123.52$$

$$\bar{x}_2 = \frac{540.4 + 849.2}{2} = 694.8$$

$$A_3 = \frac{1}{2} \times (972.8 - 849.2) \times 0.4 = 24.72$$

$$\bar{x}_3 = \frac{849.2 + 972.8 + 849.2}{3} = 890.4$$

Therefore, defuzzified value

$$x^* = \frac{(21.68 \times 540.4) + (123.52 \times 694.8) + (24.72 \times 890.4)}{21.68 + 123.52 + 24.72}$$
$$= 703.56$$

Hence, active consumption is 703.56Wh. Similarly, the idle mode energy consumption was computed to be 431.98Wh while the off- mode energy consumption was evaluated to be 34.0Wh.

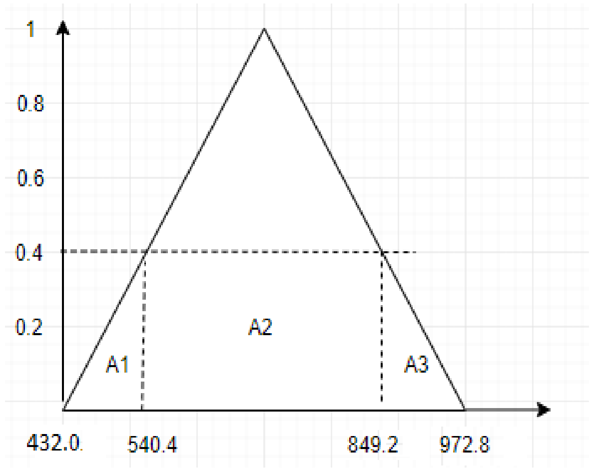

Fig -10. Triangular function for evaluating active consumption.

Stage 6: The weekly energy consumption for the desktop computer which is the sum of the active mode energy consumption, idle mode energy consumption and off mode energy consumption is therefore equal to 1169.54Wh. Therefore, the estimated energy consumption for four weeks is 4678.16Wh (i.e., 1169.54 × 4). The obtained weekly energy when the input data was keyed into the proposed algorithm in MATLAB was 1169Wh. Thus, the value computed by hand is not significantly different from that generated from MATLAB.

A surface viewer and rules viewer from MATLAB, for the case presented, are shown in Fig -11 and Fig -12.

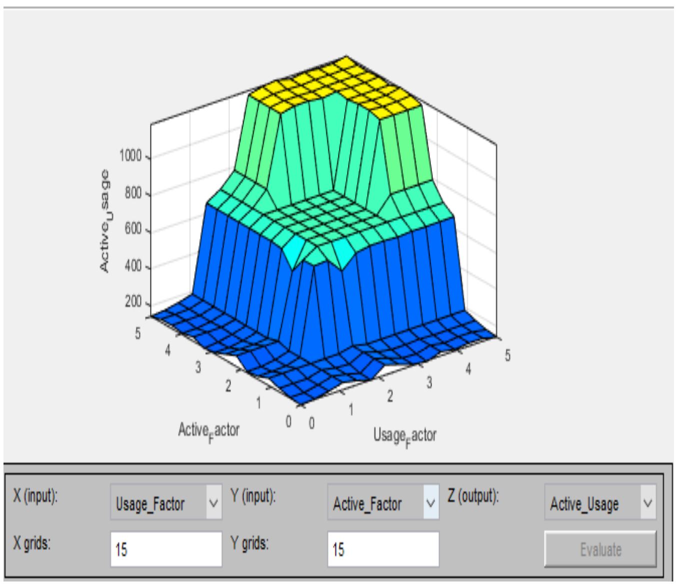

Fig - 11. MATLAB Surface viewer for the active usage of desktop computer for the developed FIS

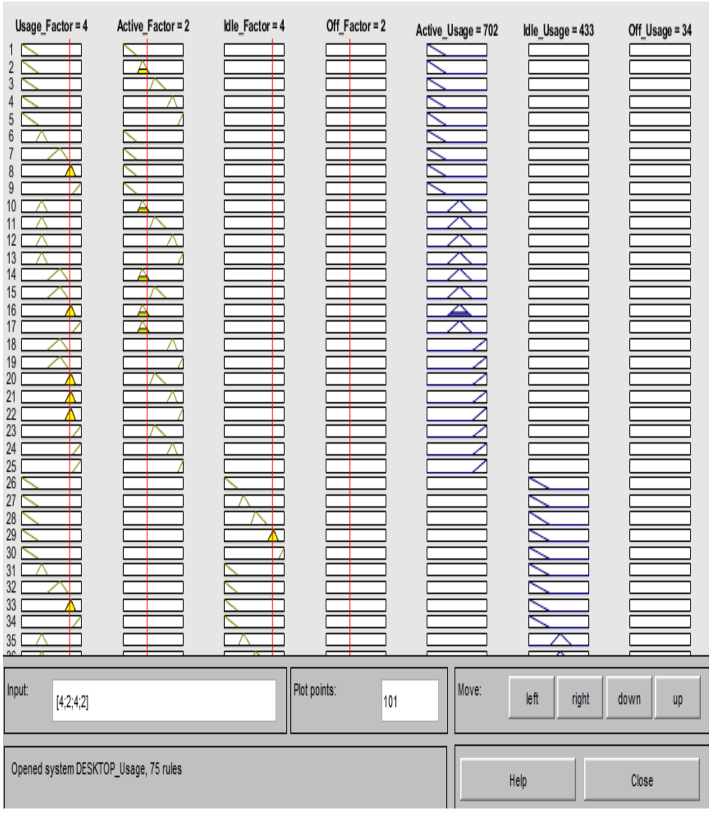

Fig -12. A MATLAB Rules viewer for the developed FIS

9.3 Comparison of energy estimates with measured data

Sample results are presented to demonstrate the performance of the proposed method. Table 8 shows the estimated energy for the monitored UELs for a four-week period, at the office of the Administrative Assistant (AA) of the Department of Civil Engineering (DCE). Fig -13 shows a comparison between the estimated total energy usage for each of the UELs and the measured energy usage for the same period. It is noted from Fig -13 that the estimated energy consumption closely matches the measured values. The least error in estimation, computed using (9) was -3.52%. This error relates to the estimate for the photocopier. The highest error was 5.96% and it relates to the printer. Table 9 shows the estimated energy for the monitored UELs for a four-week period, at the office of the AA at the Department of Geological Engineering (DGE). Fig -14 compares the measured and the estimated energy over a four-week period at the office of the AA at DGE. From Fig -14, the estimated energy does not deviate much from the measured energy. The least error in estimation was 2.23%, for the photocopier, while the highest error was 7.48%, for the desktop computer.

$$Error\ in\ estimation = \frac{Measured\ energy - Estimated\ energy}{Measured\ energy}$$

(9)

Table -8. Estimated energy (Wh) for a four-week period for UELs at the office of the AA at DCE.

UEL	Active mode usage (Wh)	Idle mode Usage (Wh)	Off mode Usage (Wh)	Total energy (Wh)
Desk. Comp.	2808	1732	136	4676
Laptop	2164	100.4	27.68	2292.08
Printer	872	712	1232	2816
Photocopier	1828	142.4	608	2578.4

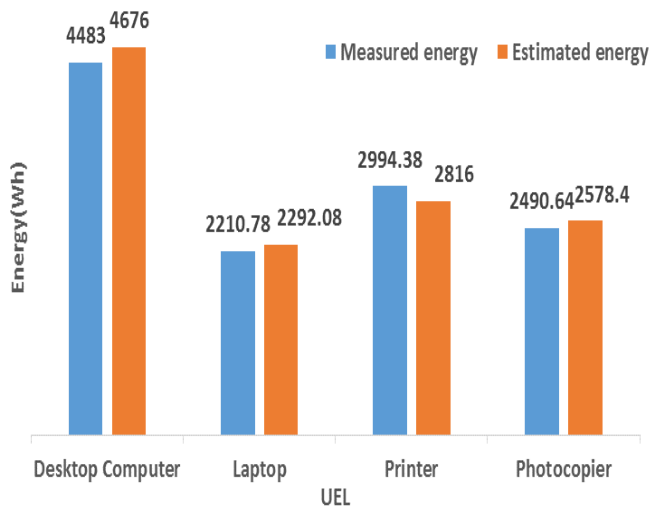

Fig -13. Measured and estimated energy for a 4-week period at the office of the AA at DCE.

Table -9. Estimated energy (Wh) for a four-week period for UELs at the office of the AA at DGE.

UEL	Active mode usage (Wh)	Idle mode Usage (Wh)	Off mode Usage (Wh)	Total energy (Wh)
Desk. Comp.	780	1732	239.2	2751.2
Printer	872	208.8	1232	2312.8
Photocopier	548	142.4	608	1298.4

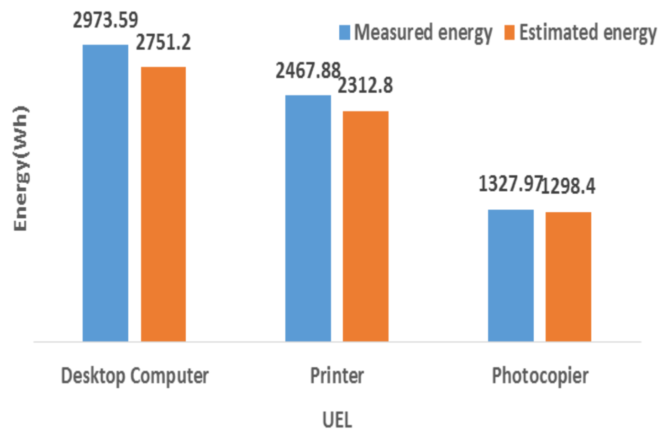

Fig -14. Measured and estimated energy for a 4-week period at the office of the AA at DGE.

Table -10. Estimated energy (Wh) for four weeks for UELs at LB33.

UEL	Active mode usage (Wh)	Idle mode Usage (Wh)	Off mode Usage (Wh)	Total energy (Wh)
Desk. Comp.	780	1024	239.2	2043.2
Laptaop	596	339.6	182.8	1118.4
Printer	872	208.8	1232	2312.8

Table 10 provides details of estimated energy over a four-week period for the studied UELs at LB33. Fig -15 compares the estimated energy with the measured energy. It can be observed from Fig -15 that the estimated energy closely follows the measured energy. Here, the least error in estimation was 3.52% which relates to the laptop. The highest error was 11.23% and it relates to the desktop computer. Table 11 shows the energy estimates for a four-week period for the studied UELs at LB36. Fig -16 also compares the estimated energy to the measure energy. It is noted from Fig -16 that the estimated energy closely matches the measured energy. The errors in estimations for the desktop computer and laptop were 6.80% and 5.41% respectively.

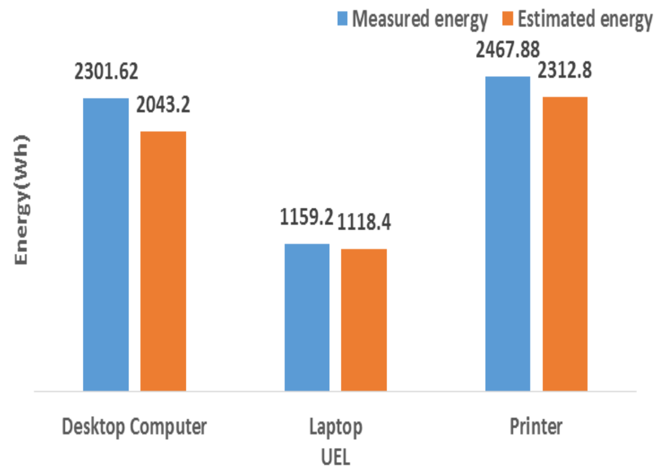

Fig -15. Measured and estimated energy consumption for four weeks at LB33.

Table -11. Estimated energy (Wh) for four weeks for UELs at LB36.

UEL	Active mode usage (Wh)	Idle mode Usage (Wh)	Off mode Usage (Wh)	Total energy (Wh)
Desk. Comp.	780	309.6	239.2	1328.8
Laptop	596	100.4	27.68	724.08

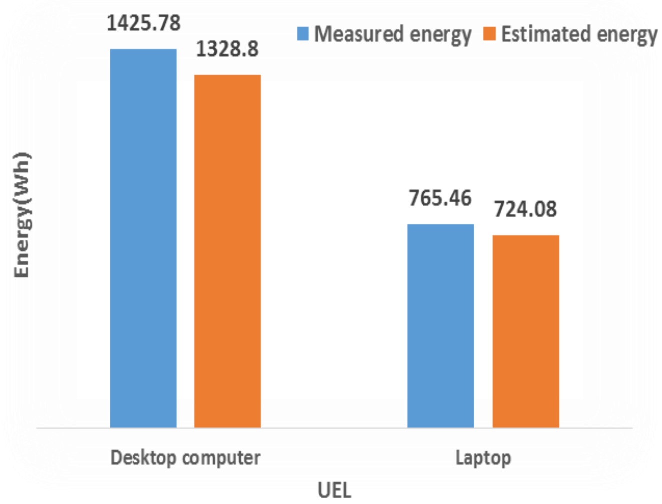

Fig -16. Measured and estimated energy consumption for four weeks at LB36.

10. CONCLUSIONS

A technique for estimating the energy consumed by UELs in operational office buildings has been presented. The technique offers a simple and low-cost approach to UEL energy estimation. Although the development of the technique required field measurements, its subsequent usage for energy estimation does not require the use of measuring instruments or occupancy sensing devices. The technique overcomes the cumbersomeness, complexity and costly nature of existing methods. The margins of error in energy estimation could be as low as 2.23%. The estimation errors for laptops, printers and photocopiers were less than 6%. However, for desktop computers, the error could be as high as 11.23%. Therefore, improvements are needed to reduce the margins of error. Future work will fine-tune the method to produce very low estimation errors, particularly, for desktop computers.

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