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Cognitive internet of things-based framework for efficient consumption of electrical energy in public higher learning institutions

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Abstract

Electric energy is widely used to power homes, businesses, industries, and Higher Learning Institutions. However, the behavioral trend of using electricity poses challenges in saving energy. Most HLIs electricity users do not switch-off electrical appliances such as lights, fans, and air conditioners when not in use, resulting in high electricity bills and a shorter equipment life span. The literature indicates that misuse of electrical power is more of a behavioral matter, which can be challenging to control. In such scenarios, technological intervention is needed to minimize human interaction. Therefore, this work developed a Cognitive Internet of Things (CIoT)-based framework for efficient consumption of electrical energy in HLIs. CIoT has been applied in the context of saving electrical energy. The proposed framework uses the Linear Regression model for training to monitor air conditioners, fans, and light bulbs. The model compared measured values with established thresholds to perform the necessary actions. Training results from the Linear Regression model show that the air conditioning model achieved an of 97.5%, a chi-square, R^2, value of 0.450, a standard error of 0.524, and a "*t*" value of − 4.638% accuracy. The model for fans scored 97.5% accuracy with a chi-square, R^2, of 0.314, a standard error of 8.58×10^{-11}, and a "*t*" value of 5.229. On the other hand, the lighting model scored an accuracy of 97.5% with a chi-square, R^2, of 0.298, a standard error of 0.396, and a "*t*" value of 0.311. All scenarios for testing the model using real data were successfully achieved 100%.

Keywords: Cognitive Internet of Things, CIoT framework, Linear regression, Electrical energy efficiency

Introduction

Electrical power is a critical factor in any nation's long-term development and the primary tool for a stable economy [23]. Tanzania, through its national utility company, Tanzania Electric Supply Company (TANESCO), generates around 1600 MW of which 39.46% is connected to the national grid [24]. The generation capacity in Tanzania is not sufficient to meet the current energy demand, especially now with the newly developed policy of the "Tanzania for Industrialization" campaign. In addition, the generated power is not efficiently used, especially in public sectors, including HLIs, where significant power is wasted, causing unnecessary higher electricity bills.

Research shows that in the USA, public buildings consume 30–40% of the electrical power produced worldwide, while commercial buildings consume 18% of the total generated energy. It is estimated that $2.8 billion is wasted each year as a result of computers, air conditioners, lights, and fans being left on at night and on weekends, which also causes pollution and carbon emissions [6, 14].

Efficient use of electric energy can reduce energy consumption, consequently saving customers' money and boosting economic welfare [7]. Energy-saving behavior is often influenced by monetary incentives and should not be generalized into an office building context whereby the users have no financial responsibility for their utility expenses [13]. OzU [15] claimed that if the occupants are directly involved in the payment of the energy bills, their usage behavior should be more radical than those who are not.

Barriers to energy behavioral change may be caused by employees not paying for the energy bills, being unaware of the office energy demands, or not seeing any direct benefit from energy savings [19]. The literature indicates that relying on behavioral change may not be a practical solution to energy savings [8]. According to Karjalainen [10], HLIs users may only save energy if they are incentivized by introducing bonuses and gifts. Alternatively, HLIs have to control their employees' energy consumption by installing smart appliances and automating peak load management. Efficient management of electrical power consumption by both private and public organizations needs the integration of Information and Communication Technology (ICT) on the consumers' demand side [4]. In this work, a Cognitive Internet of Things (CIoT)-based framework for efficient consumption of electrical energy for HLIs has been developed. The framework is trained using Linear Regression models for air conditioning (AC), fans, and lighting. The models compared measured values with established thresholds to take the necessary actions so as to optimize power usage in the HLIs.

This paper created a CIoT framework based on linear regression to address the issue of electrical energy efficiency in public buildings. Due to the study time limit, it was not easy to test the model in a real environment; instead, Proteus simulation software was used to test its performance. Based on its 97.5% performance accuracy, its use in a real-world environment will result in overall electrical control, saving energy, lowering electrical bills, and saving money.

The proposed framework was based at the College of Information and Communication Technology (CoICT) of the University of Dar es Salaam in Tanzania, which is a public institution with essential equipment for this study, including fans, air conditioning, and lighting. Data were gathered using a questionnaire, observation, and document analysis. During data collection phase, meteorological weather data for a year were also used. This research adopted content analysis methods for data analysis. Supervised linear regression and machine learning were used to extract comprehended information from data using semantic knowledge. In order to evaluate the framework, the study used Proteus simulation software. The Python language, written on Jupiter Notebook, was used to train the model using the customized dataset. The decision process was eventually completed utilizing machine learning through the deployment of a linear regression model for data analysis. Using simulation, the trained model was then prepared to receive real, measured data in the room and see if it would produce the expected results.

The remaining parts of the paper start with the literature review, where CIoT technology, CIoT architecture, and related works are explained. The analyses of existing CIoT frameworks that followed assisted in developing the proposed CIoT framework, along with the dataset used to train the model. Under findings and discussion, results from a model using real-world sensed data are presented. It also shows the sample performance of a model operated for 24 hours. It should be noted that the framework was not implemented in the real environment due to the study time limit and other policy issues.

Literature review

The Cognitive Internet of Things technology

Currently, the Internet of Things (IoT), as an aggregation of the internet, wireless networks, and computing, is a rapidly growing technology in a business environment. IoT connects physical things like vehicles, buildings, and various devices with embedded intelligent sensors [3]. The functions performed by any of the devices or sensors are controlled by a microcontroller, and the operation is performed by any remote device or computer through the Internet.

Ploennigs, Ba, and Barry [18] revealed that CIoT architecture consist of sensing components, semantic modeling and reasoning modules, and ML modules (Fig. 1). The sensing components viewed in the perception or physical layer acquire the critical information relevant to the context of the physical systems and allow the elaboration of the semantic Metamodel of the physical world using appropriate sensors [5]. The perception block implements ML techniques for the identification of defined events [17]. The ML module uses advanced learning algorithms, built on top of existing semantic models, to provide systems with self-learning capabilities [17].

According to Atzori et al. [2], IoT is all about identification, sensing, and data communication with a vision of anytime, anywhere, and in any medium. However, the communicated data are unexpected, and the associated systems lack the major decision-making capability that a smart system requires. This triggered the emergence of Cognitive IoT (CIoT), which provides intelligence among the devices in the network. Existing IoT applications rely heavily on humans to process cognition, whereas CIoTs interact

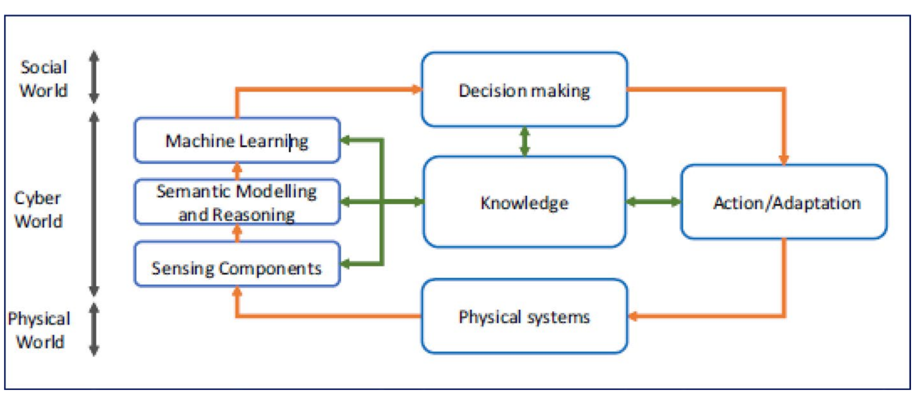

Fig. 1 CIoT architecture by Ploennigs et al. [18]

with the physical environment and/or social networks with little or no human intervention [26]. According to Wu et al. [26], CIoTs enhances the current Internet of Things by mainly integrating the human cognition process into the system design. Among many advantages, CIoTs can save people's time and effort, increase resource efficiency, and enhance service provisioning.

Related works

This paper explored four CIoT frameworks presented in the literature: A Cognitive Internet of Things Framework by Wu et al. [26], Cognitive Internet of Things Framework based on Blockchain by Saghiri et al. [20], Cognitive Internet of Things Framework based on Smart City by Park et al. [16], Cognitive IoT Framework Based on IoT Interoperability by Adesina and Osasona, [1], and an architecture for Cognitive Internet of Things and Big Data by Sassi et al. [22].

General purpose Cognitive Internet of Things framework by Wu et al. [26]

The general purpose CIoT framework proposed by Wu et al. [26] suggests that CIoT serves as a transparent bridge between the physical world and the social world to form an intelligent physical-cyber-social (iPCS) system. The cognitive process of the iPCS system consists of four major layers, namely the sensing control layer, the data semantic knowledge layer, the decision-making layer, and the service evaluation layer, as depicted in Fig. 2.

The sensing control layer, which is also known as the perceptor layer, interfaces with the physical environment in which the perceptors sense the environment by processing the incoming stimuli and feedback observations to the upper layer, and the actuators control the perceptors via the environment [26]. The data semantic knowledge layer then effectively analyzes the sensed data to form useful semantics and knowledge.

The decision-making layer, on the other hand, uses semantics and knowledge extracted from the sensing layer to enable multiple interactive agents to reason, plan, and select the most suitable action with dual functions to support services for human and social networks and stimulate action in the physical environment using ML techniques. Cognitive decision is one of the key factors of CIoT intelligence, according to Li et al. [12]. Generally, the process of decision-making in CIoT involves reasoning, planning, selecting and analyzing the collected data, and inferring useful information [21]. Performance

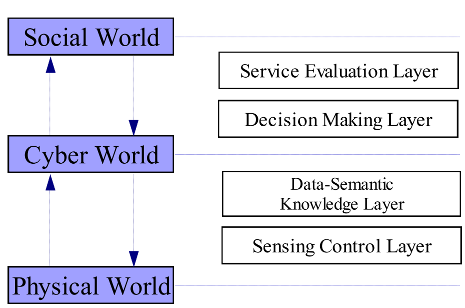

Fig. 2 General CIoT framework by Wu et al. [26]

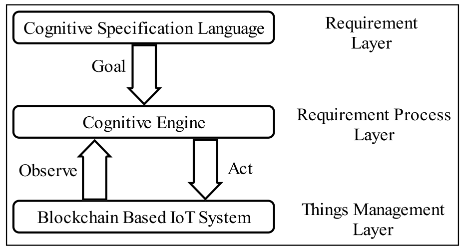

Fig. 3 CIoT based on blockchain technology *Source*: [20]

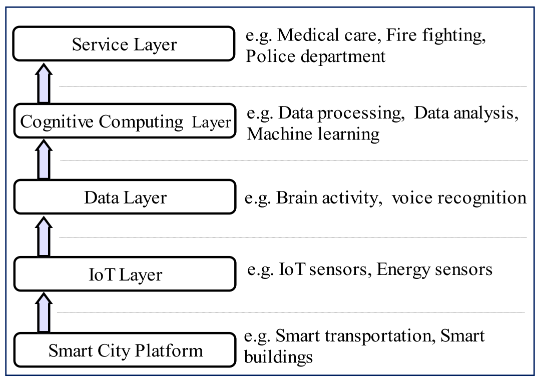

Fig. 4 CIoT-Net architecture *Source*: [16]

of the evaluation layer is based on the provisioned services and feedbacks the evaluation results to the cognition process as detailed in Wu et al. [26].

Blockchain-based Cognitive Internet of Things framework Saghiri et al. [20]

Saghiri et al. [20] proposed a blockchain-based CIoT framework (Fig. 3). According to Saghiri et al. [20], CIoT based on a blockchain framework consists of three layers: the requirement layer, the cognitive process layer, and the things management layer. In the Requirement Layer, the goal and behavior of the network may be described by a Cognitive Specification Language (CSL). The cognitive engine acts on the items' actuators, triggering a set of smart contracts that are appropriate for the situation. In the Thing Management Layer, the elements of IoT are combined with blockchain technology, and the created problem is solved by cognitive systems.

Smart city-based Cognitive Internet of Things framework by Park et al. [16]

A smart city uses CIoT technology to enhance performance, reduce costs, efficiently consume resources, and engage more effectively and actively with its citizens [16]. The IoT in smart cities encompasses smart buildings, smart homes, energy, transportation, agriculture, and industries [16]. Each component of the system has its own sensor that collects data and sends it to the IoT layer.

The IoT layers (Fig. 4) describe the received real-time sensor data from the smart city platforms. The collected data are used to optimize multiple smart city services available on the smart city platform. The Data Layer prepares data for cognitive computing-powered AI systems, and the Cognitive Computing Layer specifies the steps involved in developing a cognitive computing algorithm. The latter layer involves data processing, data analysis, cognitive trait extraction, and machine language. The service layer, on the other hand, discusses the various applications of cognitive computing in the smart city context.

Cognitive IoT framework based on IoT interoperability by Adesina and Osasona [1]
The issue of comprehensive interoperability, which caused data created from numerous application domains to be inaccessible, was one of the challenges that CIoT was employed to overcome [1]. Figure 5 illustrates the three layers of the proposed framework: the application layer, adaptive middleware layer, and cognitive communication layer. Fog-based distribution methods were adopted for implementing the IoT gateway. In the application layer, sensor devices were capable of sharing the information and feeding it to the adaptive middleware layer as an instantiated multi-protocol.

Cognitive Internet of Things and big data by Sassi et al. [22]
Sassi et al. [22] developed an architecture for Cognitive Internet of Things and Big Data. After analyzing the data processing within proposed existing technologies at the related work section, they dealt with the variety of data and transmit collected data to a structured data that can be analyzed. As shown in Fig. 6:

- In the first and second layer, a tool was required to collect data from various sources using smart device features such as human sensors, user input, documents, environmental sensor, localization and movement. This tool can extract and recognize data from unstructured data which is a big challenge for smart devices.
- In the knowledge and decision-making layer, the output data from the tool and other data can be extracted and loaded into a central storage.

Proposed CIoT framework for efficient electrical power consumption
Analysis of existing CIoT framework layers
Existing CIoT frameworks have a different number of layers depending on the application. However, some layers have common functionalities. Wu et al. [26] proposed four layers, while Saghiri et al. [20] and Adesina and Osasona [1] have three layers, Park et al. [16] have five layers, and Sassi et al. [22] have 4 layers. The first layer, in all studies, is a physical layer that includes the use of sensors to collect environmental data. This layer is

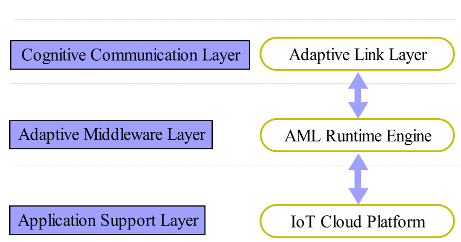

Fig. 5 Cognitive IoT gateway framework *Source*: [1]

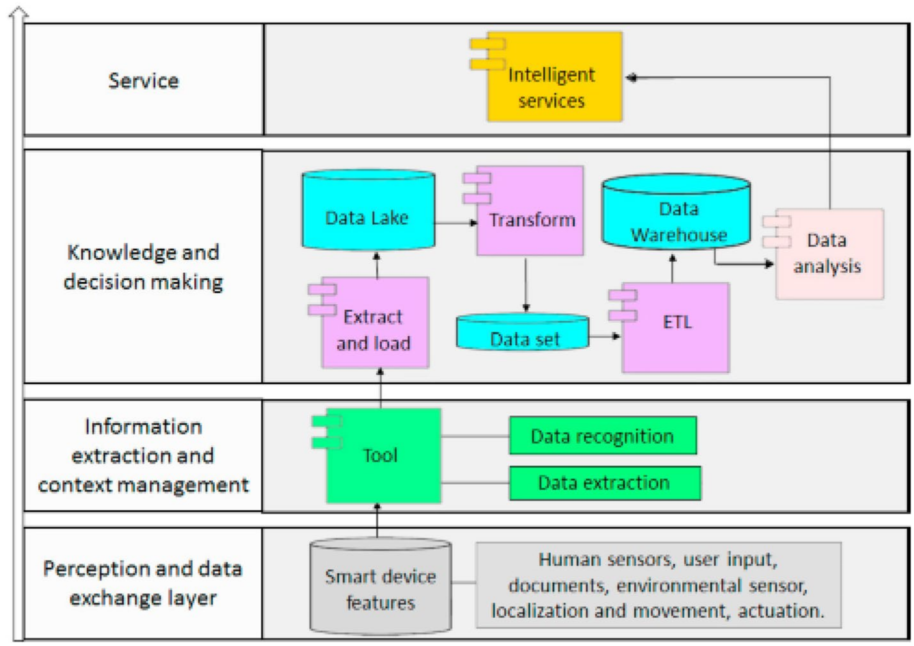

Fig. 6 Framework for Cognitive Internet of Things and big data by Sassi et al. [22]

critical in an IoT system as it creates data and all subsequent processes begin. The perception/sensing layer is directly connected to the physical environment and influences the decision-making process. This is also used by Park et al. [16] and Wu et al. [26]. Once the data are collected by processing the incoming stimuli and providing feedback to the layer on top, the perceptors can control the environment. In the context of controlling electrical power consumption, several sensors such as voltage, current, power, and relay switches are often employed. As a result, the proposed framework for electrical power consumption uses a physical layer, also called the perception layer, as its first layer.

The second layer describes the process of acquiring data semantic understanding. All frameworks except that of Saghiri et al. [20] included this layer. Wu et al. [26] employed a data semantic layer to analyze the data collected from the physical layer with the help of ML algorithms. In [1, 16], layer two involves data management and analysis using different techniques in AI. In this regard, the proposed framework also uses ML to implement the layer.

With the exception of Saghiri et al. [20], the third layer is the decision layer. This layer entails reasoning, planning, and selecting the best course of action based on the gained semantic knowledge. The last layer, known as the service evaluation layer, which integrates social networks, is only discussed by Wu et al. [26]. This layer will not be adopted since it is incompatible with the concept of energy efficiency in this context.

Proposed CIoT framework layers for efficient electrical power consumption

This study proposed an effective CIoT framework to control the electrical power usage in HLIs. The proposed framework consists of three layers: the physical or perception layer; the knowledge acquisition layer; and the control layer, as illustrated in Fig. 7.

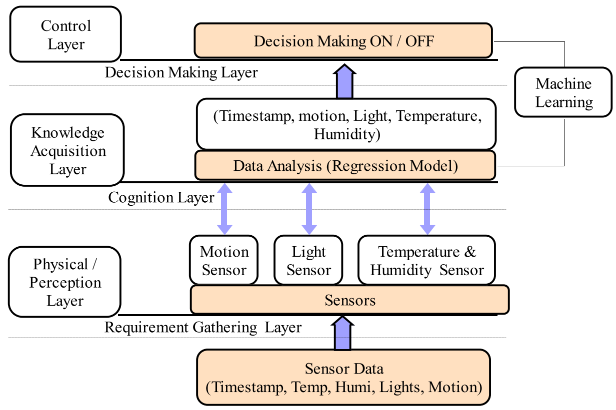

Fig. 7 Proposed CIoT framework

Physical/perception layer

The physical layer includes the use of sensors to create and collect environmental data. The physical layer, as shown in Fig. 6, detects the motions of the users while using the class rooms and checks the light intensity and ambient temperature using appropriate sensors. Motion sensors sense the existence of a person in a room and activate the system accordingly. Light sensors check the intensity of the light and inform the system to take appropriate action while the temperature and humidity sensors gather the atmospheric temperature and humidity. When a person enters the room, the surrounding temperature needs to be known and compared with a threshold level for the system to make informed decisions. For example, if the temperature is below the threshold but the humidity is high, then only fans may be activated, and if the temperature and humidity are both above threshold levels, both the fan and the air conditioner may be activated.

Knowledge acquisition layer

The upper second layer is the most effective layer, which accepts collected data for analysis. Once the data are analyzed using different technologies such as ML, supervised, unsupervised, or reinforcement learning, in this context, knowledge is extracted under the data analytics part. Unlike in [26] and [16], where data have to be understood by semantic derivation and knowledge discovery, which is not applicable in the context of electrical power in buildings. According to Wu et al. [26], with massive data analytics, tremendous perceived data about physical world, cyber world, and social world in CIoT are well processed into an organized manner. However, as CIoT envisions trillions of objects to be connected and function cooperatively, it is still not feasible to utilize these analyzed data for decision-making directly due to both complexity and inefficiency. As one can imagine, only if the objects within CIoT are able to understand correctly and reason properly can they behave appropriately. Knowledge Acquisition Layer carries the whole process of learning and analyzing the collected data. This is the cognition layer, and a multiple linear regression model is used in Machine Learning.

Control layer

The control layer ensures the correct decision, based on the knowledge gathered from the lower layer. The layer employs knowledge data to allow multiple, even massive interactive agents to choose the best action. In this context, decision-making is based on switching on/off electrical appliances such as air conditioning, lighting, and electric fans, depending on the presence of a human being. Threshold values of 24 °C for temperature, 30–50% for humidity, and 400–500 lumens for rooms, as recommended by Lennox [11], were used in the control layer for decision-making when they were below or above.

Linear regression model and dataset

Linear regression has a wide range of applications, including prediction, forecasting, or error reduction. Linear regression can be used to fit a predictive model to a data collection of observed data and descriptive variables. The study used four dependent variables for prediction: timestamp, temperature measurement, light level, and humidity, with AC status, light status, and fan status acting as independent variables. The Linear Regression equation is given by Uyanik and Guler [25]:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon$$

where y is the dependent variable, x_i with $i = 1, 2, \ldots n$ are the independent variable, $\beta_j, j = 0, 1, 2, \ldots n$ is the parameter and ε is the error.

The model used a sensor dataset shown in Table 1 (part of the dataset for air conditions). The dataset includes the Tanzania Meteorological Authority (TMA) timestamp, temperature, and humidity values. Dar es Salaam is a humid city with relatively hot weather. High humidity is experienced in March, April, and October to November, whereas the hot season begins from May to October, then January to mid-March. Through a multiple linear regression model, the sensor data were used to guide the hot time or high humidity time by monitoring the temperature. If, for example, the sensor registers high humidity, which suggests that the environment is hot, then the regression model will predict that the AC should be turned on. Fig. 8 shows the summary results of a model for air conditions.

Table 2 represents the dataset and its corresponding results for fans which are shown in Fig. 9. Table 3 represents the dataset and its corresponding results for lighting as shown in Fig. 10.

Table 1 A sensor dataset

Timestamp	Ac status	Motion	Temperature	Humidity
20210810060001	1	1	29	85
20210810070001	1	1	31	84
20210810080001	1	1	30	86
20210810090001	1	1	29	83
20210810010001	1	1	31	85
20210810011001	1	1	28	80
20210810012001	1	1	27	82

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               Acstatus   R-squared:                       0.450
Model:                            OLS   Adj. R-squared:                  0.432
Method:                 Least Squares   F-statistic:                     25.89
Date:                Tue, 22 Mar 2022   Prob (F-statistic):           2.52e-12
Time:                        13:36:32   Log-Likelihood:                -37.173
No. Observations:                  99   AIC:                             82.35
Df Residuals:                      95   BIC:                             92.73
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const          -2.4300      0.524     -4.637      0.000      -3.470      -1.390
Timestamp    3.371e-16      2e-14      0.017      0.987   -3.93e-14       4e-14
Temperature     0.0613      0.013      4.844      0.000       0.036       0.086
Humidity        0.0158      0.002      6.960      0.000       0.011       0.020
================================================================================
Omnibus:                        0.142   Durbin-Watson:                   1.345
Prob(Omnibus):                  0.931   Jarque-Bera (JB):                0.008
Skew:                          -0.019   Prob(JB):                        0.996
Kurtosis:                       3.021   Cond. No.                     2.92e+14
==============================================================================
```

Fig. 8 AC model results

Table 2 Fans sample dataset

	Timestamp	Fan status	Motion	Temperature
0	20210810060001	1	1	24.0
1	20210810070001	1	1	25.0
2	20210810080001	0	1	22.0
3	20210810090001	0	1	29.0
4	20210810010001	0	1	31.0

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              Fanstatus   R-squared:                       0.314
Model:                            OLS   Adj. R-squared:                  0.300
Method:                 Least Squares   F-statistic:                     22.01
Date:                Thu, 31 Mar 2022   Prob (F-statistic):           1.35e-08
Time:                        12:22:23   Log-Likelihood:                -25.248
No. Observations:                  99   AIC:                             56.50
Df Residuals:                      96   BIC:                             64.28
Df Model:                           2
Covariance Type:            nonrobust
================================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const        4.484e-10   8.58e-11      5.229      0.000    2.78e-10    6.19e-10
Timestamp    5.211e-14   1.62e-14      3.224      0.002       2e-14    8.42e-14
Motion          0.3375      0.065      5.219      0.000       0.209       0.466
Temperature    -0.0379      0.012     -3.253      0.002      -0.061      -0.015
==============================================================================
```

Fig. 9 A summary results for a fan model

Flow of information for the proposed CIoT framework

Three sensors were placed in a room to monitor the temperature, motion, and light intensity. They are used to collect real-time data and enable the model to predict the

Table 3 Lightings dataset

Timestamp	Light status	Motion	Lumens
20210810060001	0	1	320
20210810070001	0	1	500
20210810080001	0	1	350
20210810090001	0	1	566
20210810010001	0	1	700
20210810011001	0	1	800
20210810012001	0	1	900
20210810013001	0	1	850
20210810014001	0	1	740
20210810015001	0	1	600
20210810016001	0	1	503

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            Lightstatus   R-squared:                       0.298
Model:                            OLS   Adj. R-squared:                  0.276
Method:                 Least Squares   F-statistic:                     13.46
Date:                Wed, 23 Mar 2022   Prob (F-statistic):           2.17e-07
Time:                        20:15:11   Log-Likelihood:                -36.055
No. Observations:                  99   AIC:                             80.11
Df Residuals:                      95   BIC:                             90.49
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.1230      0.396      0.311      0.757      -0.663       0.909
Timestamp   1.783e-14   1.98e-14      0.901      0.370   -2.14e-14    5.71e-14
Motion         0.3494      0.110      3.162      0.002       0.130       0.569
Lumens        -0.0014      0.000     -5.981      0.000      -0.002      -0.001
==============================================================================
```

Fig. 10 Light model summary results

decision. The first model was trained to control air conditioning using timestamps, temperature, humidity, and motion datasets. The second was trained to control fans' operation using timestamp, motion, and temperature datasets, while the third model was trained to monitor and control lights using luminous, timestamp, and motion. The measured values are sent to the linear regression model trained by the customized datasets in Tables 2, 3, and 4. The expected output is the actions given by the pre-determined criteria of the trained model threshold values of 24 °C for temperature, 30–50% for humidity, and 400–500 lumens as recommended by Lennox, [11]. Figure 11 shows the flow of information for the model, and Fig. 12 shows the block simulated circuit for the CIoT system for efficient consumption of electricity.

Findings and discussion

Figures 8, 9 and 10 are results obtained after training the regression model for air condition, fan and lighting respectively, in python using Jupyter notebook.

Table 4 Comparison of CIoT based on context of application, and number of layers

S.No.	CIoT framework with context of application	Total layers	Layer names
1.	The general CIoT Framework by Wu et al. [26]	4	Sensing control Data – Semantic Knowledge Decision-making Service evaluation
2.	CIoT based on Blockchain by Saghiri et al. [20]	3	Requirement Cognitive process Things management
3.	CIoT Gateway Framework by Adesina and Osasona, [1]	3	Cognitive communication Adaptive middleware Application
4.	CIoT based on Smart City Network by Park [16]	5	Smart city platform IoT Data Cognitive computing Service
5.	Cognitive Internet of Things and Big Data by Sassi et al. [22]	4	Perception and data exchange Information extraction and context management Knowledge and decision-making Service
6.	CIoT-based framework for efficient consumption of electrical energy	3	Physical/Perception Knowledge acquisition Control

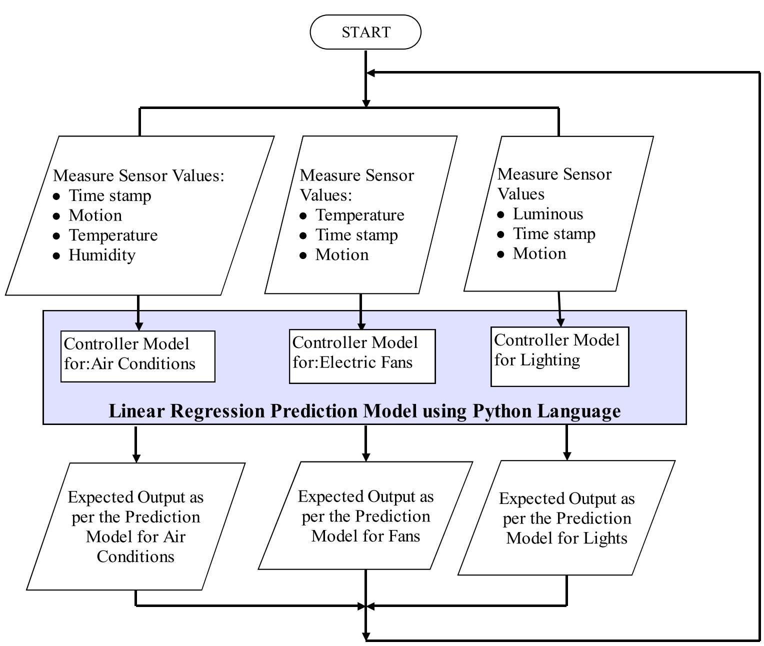

Fig. 11 Flow of information for the proposed CIoT framework

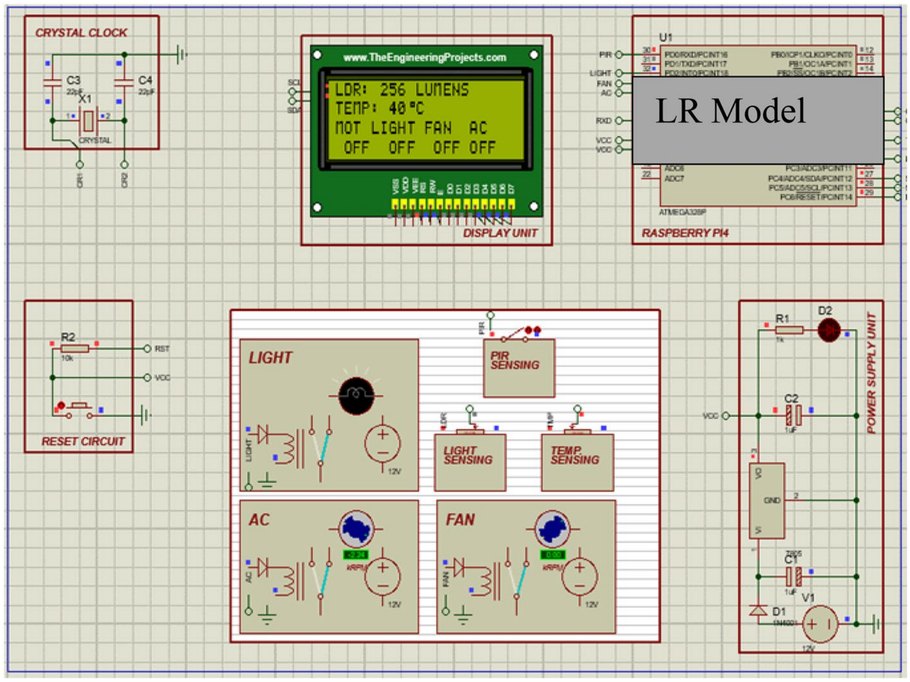

Fig. 12 Simulated circuit for CIoT system for efficient consumption of electricity

- For air condition, the model results as indicated in Fig. 8 show the chi-square R^2 score to be 0.6122830441059741 which means that the model performed well according to Flexlet, [9] standard values. The model standard error was measured as 0.429, with "t" value measured as -2.863. The model accuracy in Fig. 8 scored 97.5% and proven to work as expected.
- For fans, the model results as indicated in Fig. 9 show the R^2 measured 0.314 whereas standard error was 8.54e−11 and t values were 5.229. The model accuracy in Fig. 9 scored 97.5% and proven to work as expected
- For lighting, the model results as indicated in Fig. 10 show that the computed model's chi-square R^2 score was 0.298, with a standard error of 0.396 and "t" value of 0.311. The model accuracy in Fig. 10 also scored 97.5% and proven to work as expected

Results from the prediction model using measured data from a given room in comparison with the threshold values set are presented in this section using a display unit as follows:

- The prediction model output (Fig. 13) had all parameters OFF for light, fan, and AC when the temperature was 40 °C (above the threshold to allow ACs and/or fans to be ON) but no motion was detected.
- Fig. 14 shows that the temperature was 18 °C with a light intensity of 410 lumens and that motion was detected but the lights, fans, and air conditioner were off.
- In Fig. 15, the light intensity was 215 lumens, and the temperature was 18 °C and motion was detected. The fans and air conditioner were turned off, but the lights were turned ON.

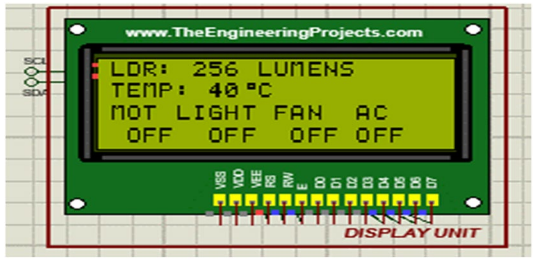

Fig. 13 No movement detected and no action has been taken

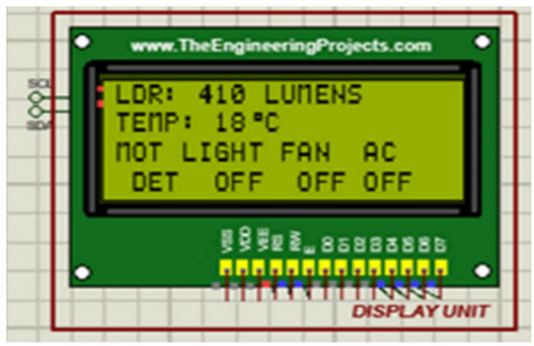

Fig. 14 Motion has been detected but no action has been taken

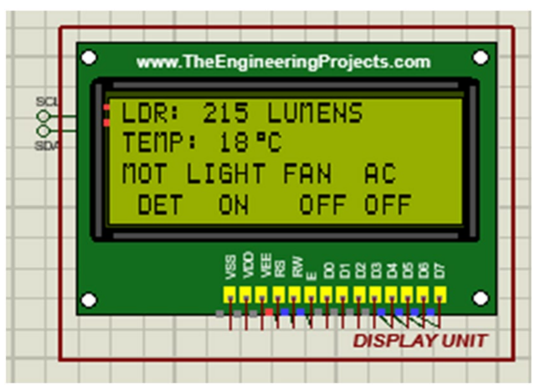

Fig. 15 Lights turned ON

- In Fig. 16, the light intensity was 451 lumens, and the temperature was 25 °C. When motion was detected, fans ran while other electrical appliances were turned OFF.
- In Fig. 17, the light intensity was 451 lumens, and the temperature was 45 °C and the motion was detected, the air conditioners were turned ON.
- In Fig. 18, the light intensity was 256 lumens, and the temperature was 40 °C and the motion was detected, lights and the air condition have been turned ON.

Figure 19 shows a sample energy-saving graph of 24 hours in which all electrical appliances are turned OFF at night and no power is utilized from 7:00 p.m. to 6:00 a.m. Power

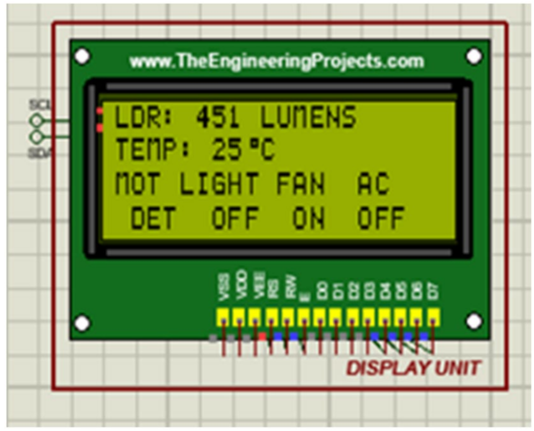

Fig. 16 Fans are turned ON

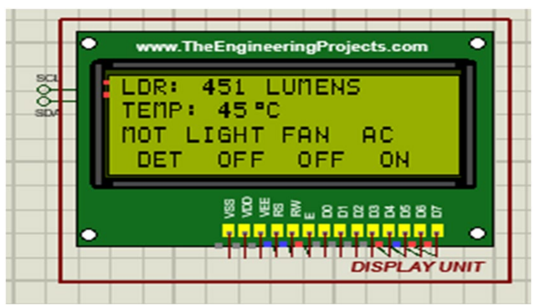

Fig. 17 Air conditioner switched ON

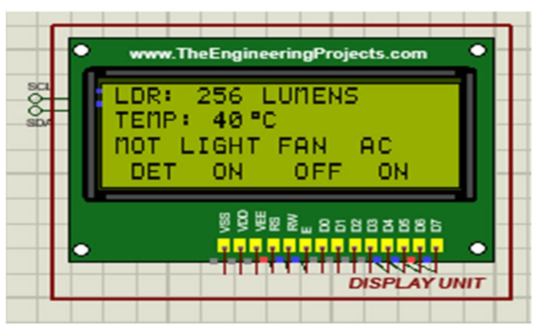

Fig. 18 Lights and AC turned ON

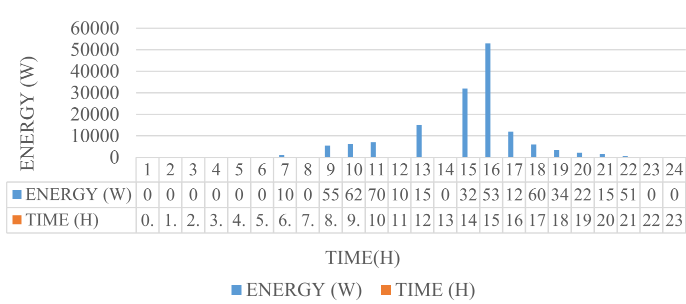

Fig. 19 Energy consumption taken on 24/9/2021

is consumed in the morning and afternoon, depending on the sensor data and motion sensors. Owing to college sessions, it is expected that students and staff would use energy during the midday hours, and due to the surrounding heat, either a fan or an air conditioner is ON.

Discussion

All CIoT frameworks have standard layers to accommodate the sensing of data, analysis or extraction of useful information from sensed data, producing necessary appropriate action/s needed from analyzed data and finally producing a final report as the output result of a framework. Based on the context of application, these layers can differ in number, some may be combined or merged and some may be broken into more layers accordingly. From related works and as shown in Table 4, Wu et al. [26] proposed four layers as the general CIoT framework, Saghiri et al. [20] have 3 layers for CIoT based on Blockchain, Adesina and Osasona [1] have three layers for CIoT Gateway Framework, Park et al. [16] have five layers for CIoT based on Smart City Network, and Sassi et al. [22] in Cognitive Internet of Things and Big Data have 4 layers. CIoT framework for Efficient Consumption of Electrical Energy comes up with three layers.

The customized dataset, which included TMA data, was used to train the linear regression prediction model. The training scored 97.5% when considering the control of all equipment: air conditioning, fans, and lighting. The chi-square R^2 scores were 0.6123 and 0.314 for air conditioning and fans, respectively, and when controlling lighting alone, it was 0.298. For fans, the model standard error is 8.54 e − 11, with a "*t*" value of 5.229. The model standard errors were measured at 0.429 with a "*t*" value of − 2.8635.229 for ACs, while a standard error of 0.396 and a "*t*" value of 0.311 was obtained for lighting. The *t*-value being the size of the difference relative to the variation in sample data. With these values obtained through linear regression prediction, the model performed well according to Flexlet's [9] standard values.

The introduction of sensors, microcontrollers, and ML models (multiple linear regression models) for learning some of the data from TMA and correlating it with the real-time sensor data and making appropriate decisions to turn ON or OFF devices solved the problem of inefficient electricity consumption and is proven to efficiently control energy usage in public buildings through the introduction of cognitive IoT-based frameworks. All scenarios for testing the model were successfully achieved at 100%.

Conclusions

Tanzania's climate, particularly in Dar es Salaam, is characterized by extended hot and sunny seasons. As a result, air conditioning and electric fans are extensively used in institutional offices. Unlike electronic equipment that consumes insignificant power while hibernating, air conditioning, lighting, and electric fans register high overall power if inefficiently used for an extended period of time. In public institutions, including HLIs, there is a tendency to leave equipment such as AC, fans, and bulbs ON even when nobody is in the office rooms, especially after power outages. It is undeniable that individuals are cautious when using electricity at home and not in public institutions like HLIs, which is directly linked with people's behaviors.

The study is suggesting that intervention to make people change their behavior toward using electrical power is one way, but its impact is not promising as people are forgetful. We need technological intervention and fewer user interventions to control electrical power, primarily in public organizations. The developed model will enable HLIs to control the usage of electrical power and will lead to savings on the high costs used to pay electrical power bills. The saved amount can be used to solve many other issues in the institutions; it will also enable utility companies to supply the saved energy to other demanding customers.

Abbreviations

AC	Air condition
AI	Artificial intelligence
AMI	Automated meter infrastructure
CIoT	Cognitive Internet of Things
CSL	Cognitive specification language
HLIs	Higher learning institutions
ICT	Information and communication technologies
IoTs	Internet of things
iPCS	Intelligent physical-cyber-social
ML	Machine learning
SCADA	Supervisory control and data acquisition
TANESCO	Tanzania electric supply company
TMA	Tanzania meteorological authority

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Author contributions
SB performed data collection and analysis. EK wrote the initial draft of the manuscript, KI reviewed the manuscripts and AA performed intensive review of the manuscript. All authors have read and approved the manuscript.

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Declarations

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Competing interests
The authors declare that they have no competing interests.

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