Individual Load Monitoring of Appliances for Home Energy Management System

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***Abstract*—Home energy management starts with a monitoring system for the user to become aware of how much energy he/she consumes over a period of time and a controlling system that maximizes energy efficiency. There are two methods of load monitoring used in analyzing loads in residential installations and one of them is Intrusive Load Monitoring (ILM). This study was aimed to create an energy management system focusing on individual load monitoring of household appliances through ILM implementation. Wireless network technology was also utilized for data transmission and access, using Raspberry Pi 3B+ and SenseTecnic cloud host. The notification feature of the system, done through a cloud-based communication platform Twilio, is 100% successful in performing its function. Energy consumption behavior model equations for specific types of appliance loads were generated using regression analysis. All equations have relatively good fit, with R squared of 85% - 94%, and low standard error, except for the equation representing the variable load with sporadic consumption pattern. Nonetheless, there is 99% confidence in the accuracy of the energy consumption behavior. On the other hand, electric consumption of the entire smart meter costs PHP34.051 only for a month of operation. This only suggests that the system will not significantly contribute to the entire household electric energy consumption cost.**

***Index Terms*—Energy consumption behavior model, forecasting, intrusive load monitoring, regression analysis, predicted consumption**

I. Introduction

Energy management usually consists of monitoring and controlling of energy in order to conserve it. It is one of the solutions to reduce the consumption of energy immediately and directly. It develops more due to the need for conservation of energy. Energy management is commonly applied to larger buildings such as industrial and commercial buildings, but recently, it started to be used in homes.

Monitoring the energy consumption and collecting the data, analyzing the meter data to find the opportunity to reduce the energy waste, implementing the target opportunity to save energy and tracking if there is some progress in energy saving efforts are common steps in energy management. If the consumption of energy is reduced, of course, it would have a chain effect and the energy cost would be reduced and importantly, it would bring positive effect on the environment because of carbon emission reduction.

Two methods of load monitoring used in analyzing the voltage and current of loads in houses are Intrusive Load Monitoring (ILM) and Non-Intrusive Load Monitoring (NILM). NILM is a process of monitoring in which components to be used can be installed even if the wiring system in a residence has already been built. Meanwhile in ILM, the component to be used in monitoring should be installed at the same time as the installation of the wiring system. NILM is widely used because of its low-cost of installation and maintenance. Fewer components such as sensors are needed to make it less complex in installation. However, NILM is less accurate and needs improvement when it comes to recognition algorithm. Based on some studies, it sometimes yields undetected error and it cannot be reliable when detecting different kind of loads. With this, monitoring is limited in fewer types of loads. On the other hand, ILM is known for its systematic process. In this monitoring technique, all branches of appliances are connected to a power meter, hence, it has more accurate results and it is easy to identify different kinds of loads. Applying the ILM technique would provide a larger system for energy management.

Given the advantages and disadvantages of both NILM and ILM, the main objective of this study was to create an energy management system focusing on individual load monitoring of household appliances, utilizing wireless network technology. Specifically, this study was aimed to implement an intrusive method of monitoring electric consumption of individual household appliances. It was also aimed to use wireless network technology in data transmission to provide user access of the energy management system. Developing an energy consumption behavior model to be used as basis of energy saving measure using regression analysis was also targeted.

This energy management system with ILM will give more accurate results and thus, may provide a more effective energy planning and savings scheme. As the system provides consumers easy access, via the internet, of their consumption data, they would have a choice to reduce their usage of electricity. As they can track the energy via real time monitoring and know how much

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energy they consumed at that specific time, then giving an energy plan based on their consumption behavior, consumers are just one step away from reducing their energy consumption.

II. RELATED LITERATURE

Energy monitoring is one of the techniques to use energy efficiently. When there is feedback, measurement of energy consumption and information on the peak hour and pattern of energy consumption, there is opportunity to reduce energy usage and cost. Implementing energy monitoring in households can have a great impact on the consumer. The consumer can now identify opportunities to adjust its power consumption and how to conserve energy via real time monitoring system. According to [1], monitoring energy consumption is important so that consumers would be able to change habits in order to reduce the amount of electricity they are consuming and at the same time, lower their energy bill.

Since the demand for energy consumption increases, a system that is capable of controlling and reducing the consumption is much helpful to the environment, thus, the consumer needs to conserve energy based on real time information on their energy consumption. According to [2], when a system can monitor energy consumption through equipment such as personal computer and other electronic gadgets that are internet-connected, it is easy to predict the energy requirement in homes and electrical consumption can be controlled efficiently. On the other hand, the study of [3] used cloud-based software for energy monitoring, which allows a real time visualization of data about the energy consumption of the building.

There are three main elements in modern energy monitoring for smart houses. They are the load, control strategy of the loads and smart meter. One of the important devices used in energy monitoring is the smart meter. This meter can help inform the consumer of his energy cost. The common working fundamental of a smart meter is measuring and recording the usage of electricity; then the data is transmitted to electricity distributors; then energy providers make the data available to consumers via internet, so that energy usage can be monitored and managed better [4].

A. Studies on Energy Consumption Monitoring

The study of [5] is on home area-network-based consumption monitoring that can provide the information of energy usage patterns and controlling the load at home using smart metering. It consists of predicting the energy cost, load scheduler and energy consumption monitor. The load scheduler controls the load, so it can reduce the energy cost, while the monitoring consists of a smart meter and smart switches to gather the data and monitor the energy consumption in residential houses. The study was conducted due to the energy crisis and because energy demand is increasing.

According to [6], energy monitoring is one the most important aspects in energy conservation. Monitoring power consumption is needed to predict technical measures to attain minimum power consumption. Their study was on a load monitoring approach based on intrusive and non-intrusive methods of monitoring system that utilizes wireless network. It highlights different energy management approach using intrusive and non-intrusive methods. The leading application of this approach is energy monitoring automation and exploration of a smart meter.

The study of [7] is all about review disaggregation method in non-intrusive appliance load monitoring. The study pertains to home energy management system, which uses non-intrusive appliance load monitoring that has an advanced low-cost system compared with intrusive appliance load monitoring that has sensors for each appliance. The non-intrusive appliance load monitoring (NIALM) has a different method for disaggregation of load data; however, the same study shows that NIALM is unstable and needs some development for high accuracy detection.

The study of [8] shows the different ways of implementation about non-intrusive monitoring of electrical signals in non-residential buildings. It focused on load-monitoring of a large-scale system with data acquisition. The study also implemented energy monitoring of different load variations involving higher voltage and current applications.

Focused on a cloud-based sensor network for environmental monitoring, [9] studied on a network of sensors that measure a certain parameter, and these data parameters are being processed in real time. It uses a wireless sensor network with sensing nodes via wireless transmission that would save data on a cloud storage, which can be viewed via mobile application on a real time framework.

A monitoring system that is capable of processing large amounts of data using smart sensor network was demonstrated in [10]. They implemented their study on residential houses, public buildings and industrial installations. They proposed a promising smart sensor network, which can be further developed for future smart grid application, detection and analysis. However, the data they gathered in a non-intrusive smart sensor had only a time span average of 24 hours.

The work of [1] implemented a real time energy monitoring system that is cost-effective and reliable. Their system interprets and analyzes certain parameters such as voltage and energy generated by household appliances. They used a hardware device for gathering data, which is stored in cloud-based RESTful API resources. They selected DFRduino Uno microcontroller as the heart of their system, considering the type of monitoring implementation in a cost-effective way possible. That study successfully attained 94% accuracy in reading the correct energy household appliance consumption, which notifies the user in a real time feedback information via SMS notification.

One aspect in the work of [11] was the creation of an energy consumption monitoring system for residential application. They created an electric meter with an energy consumption monitor that is internet-based. They recommended the improvement of the consumption monitor by identifying the specific appliance that consumes the most energy. This improvement may be the first step in transitioning households to the smart grid. As such, this present study attempted to address the above-mentioned recommendation through the implementation of intrusive methods of electric load monitoring.

B. Data Monitoring and Signal Transmission System

Power metering has an important role in the system. Power meter gives a background about much energy is consumed per month, day and hour. It gives information about the consumption of a certain load if ILM techniques are implemented intensively. Nowadays, technology is fast evolving in terms of speed, convenience, smaller occupancy and connection to everything related to it. The new trend in power meters is smart meter.

In the study of [12], a smart meter can provide a high percentage of accuracy in measuring power; it is superior to an average meter. A smart meter has a real time data storage that can be stored on the internet. It has an automatic data reading for real time power monitoring and it can also be integrated locally in wide-range energy management system for residential units.

From electronic metering, Automated Meter Reading (AMR) emerged due to the energy utilization that can access power data remotely. Due to the fast pace of technology, AMR has evolved into a new concept called Advanced Metering Infrastructure (AMI), which enables the possibility of a two-way communication between utility and consumer. AMI has a representation system of electronic meters, advanced data storage system and bidirectional communication infrastructure [12].

In the study of [13], wireless automatic monitoring must incorporate the use of wireless sensor network (WSN) in the decision on dynamic pricing during peak hours and to eliminate illegal meter tampering. Implementing this system would give information to the user because the consumer has physical access to the meter that gives the visual meter reading. Wireless automatic metering can also be integrated into a smart wireless meter along with its application and the possibility of real-time access measurement via web application.

The metering trend nowadays includes interaction with the consumer based on the load disintegration and statistical data of the consumer. A meter must be intuitive and must provide information in a way that can be easily understood by the reader. Ref. [12] aimed the interaction of consumer, device and the utility, that their system provides through a simple interaction of load management that allows the user to regulate the consumer consumption according to their desired degree of comfort.

From these monitoring systems, an energy management system that can provide interaction with the user in suggesting energy management techniques to maximize energy efficiency was put into consideration.

C. Statistical Tools in Forecasting Methods

After energy monitoring and data gathering of power through the use of smart meter stored on the cloud or internet, the formulation of energy plan is the last process in the proposed system to have an interaction between the system and for the user to implement the formulated energy plan.

The study of [14] provides a wide scope of structure planning and energy management strategies and different parameters regarding multi-energy carriers. Their study was all about different energy schemes that shows effectiveness and advantage of the smart multi energy system designed by the optimal planning model. The optimal planning model is a general and useful model for designing structure and analyzing the operation strategies in the system.

Ref. [15] discusses long-term energy forecasting for electrical utility resource planning. Different types of energy forecasting methods and analysis by economic growth, such as electricity consumption and peak demand for two decades, are key elements in electric utilities. They conducted a retrospective analysis of load forecasts on 12 Western U.S. electric utilities to find an estimation of energy consumption and peak demand. They used data produced by integrated resource planning (IRP) from 2003 to 2007 and from that data, they gathered the energy consumption and peak demand of different load serving entities (LSEs) to form different forecasting methodologies. That study yielded an overestimation assumption because of economic growth. Sensitivity, risk analysis of load, and capacity of expansion were not integrated with proper sub sequencing implementation, resulting in a complex forecast method and mildly correlated relation.

On the other hand, the work of [16] focused on forecasting methods in energy models. Energy planning models (EPMs) contribute a bigger role in policy formation and in energy sector development. According to them, EPMs have different kinds of methods, computations, scenarios and approaches for forecasting. It usually is a vast implementation and takes a very long time to process. Moreover, [16] mentioned different forecasting methods, such as support vector machine (SVM), autoregressive integrated moving average (ARIMA), fuzzy logic (FL), linear regression (LR), genetic algorithm (GA), particle swarm optimization (PSO), grey prediction (GM) and autoregressive moving average (ARMA). In terms of accuracy, the computational intelligence (CI) methods show better performance than others, while the most common method is artificial neural network (ANN). In the same study, Biswajit and Monjur showed that hybrid methods perform better than the stand-alone ones and computational intelligence are preferable to short-, medium- and long-based temporal forecasting ranges.

As stated by [17], residential household energy consumption using regression analysis supports a great feasibility of statistical approach for model development. Their study, which used linear regression, shows promising result because of reasonable accuracy and simple implementation of their methods. They used a simple linear and multiple linear regression analysis with quadratic regression analysis performed hourly and daily from their research facility. They believe that the future of energy forecasting is moving towards the development of individual models for each house due to the availability of the smart meter and engineering software. A graphical model for predicting the future residential energy consumption was used wherein the x-axis is the electricity consumption per hour while the y-axis is the varying temperature in degrees. This graphical method was also implemented in an hourly and daily basis, incorporated with temperature that yielded a common line pattern as the range of data increases.

III. Methodology

The entire system of this project essentially consisted of an electric power meter in each branch circuit where a single appliance load is connected for the purpose of individual consumption monitoring. The electric power meter also features a notification system that gives information to the user of his current energy consumption as well as an advice to reduce energy usage of the appliance in the branch circuit as an energy saving measure once the actual energy consumption equals or exceeds the energy consumption behavior.

Fig. 1 gives an overview of the entire system. The smart meter is composed of power analyzer, microcontroller and microprocessor altogether. For each single branch of appliance, a pair of power analyzer and microcontroller is dedicated. There were pairs of power analyzer and microcontroller for every single convenience outlet where the appliance was connected. This was the method by which intrusive load monitoring was achieved.

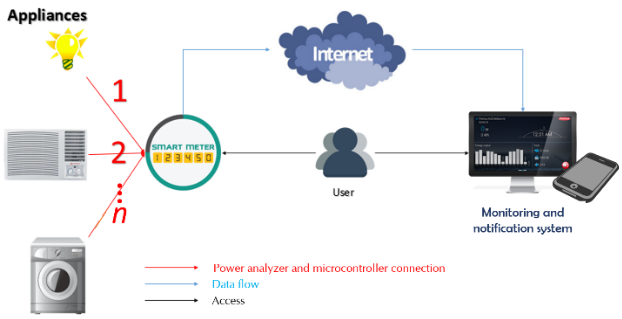

Fig. 1. Overall diagram of the home energy management system.

Each pair of power analyzer and microcontroller was connected to a single microprocessor, which processes collected data. Data is sent to the internet and from there, the user could access the data via a cloud host. The user could also get SMS notification of his actual consumption and energy saving plan, if necessary.

A. Materials, Equipment and Software

Materials, equipment and software used in this project were carefully chosen and several factors were considered. The functions of each component are discussed.

The electric power meter is the main component of the system. It features a real time power reading of each circuit branch where appliance loads are connected. The power meter measures the energy consumption of the appliance load, which is on the branch circuit that transmits data collected to the data storage database. AC Power Analyzer MKII [18] is used in this project. This is the device that measures the watt-hour consumption of the consumer. Aside from the watt-hour consumption, it can measure real and apparent power, volt RMS, amp RMS, and the power factor.

The microcontroller used for this project was Arduino Uno Rev 3 [19]. Placed on each appliance load, it processes and compares the data obtained from the power analyzer for input power data monitoring. It was also used to isolate the connection of the power analyzer to Raspberry Pi. In order to connect the serial output port of power analyzer to the USB port of Raspberry Pi, the power analyzer was used to serve that function.

The energy consumption monitoring system displays the collected data from the electric power meters for each appliance load circuit where the load is connected. The monitoring system has 4 branch circuits for the lighting outlet and another 3 convenience outlets, which are compatible to any plug type appliances. Each appliance circuit has a power meter, wherein the consumer can monitor each energy consumption per appliance. The consumer can access the monitoring system given a unique user ID and a password that corresponds to the electric meter. The Node Red system was utilized as a monitoring system because it is GUI-ready and easy to use in terms of coding. An LCD was also used to display the energy consumption of each appliance that is connected to the system. It is a 3.5-inch touch screen TFT LCD designed for Raspberry Pi. It also has an HDMI port, a resistive touch control compatible to any version of the Raspberry Pi that has Raspbian driver, multi-languages OSD menu and support HDMI audio output.

Based on the data gathered by the power meter, the system shows the consumption behavior of the consumer for the day (processed through statistical method of regression analysis). If the predicted energy consumption per branch circuit is equal or less than the actual consumption, the system will notify the user of the energy saving plan. This system works through a cloud communications platform capable of sending SMS (without a physical GSM hardware). The latest model of Raspberry Pi 3 [20] microprocessor, the model B+, was used to accommodate a larger amount of data from the power analyzer and for fast time processing.

B. Component Connections and Flow Chart

Fig. 2 shows the connection of power analyzer, Arduino and the Raspberry Pi for a single load monitoring system. The system power source was tapped into its load side, which was also 230 VAC. It was used to power the power analyzer and at the same time, it also powered the microprocessor which in turn operates the microcontroller and LCD display. On the other hand, pins RXK and RXA of the power analyzer are connected to TX0 and 3.3 V pins of the Arduino Uno, respectively. TXE and TXC pins of the power analyzer are connected to GND and RX0 pins of Arduino Uno, respectively.

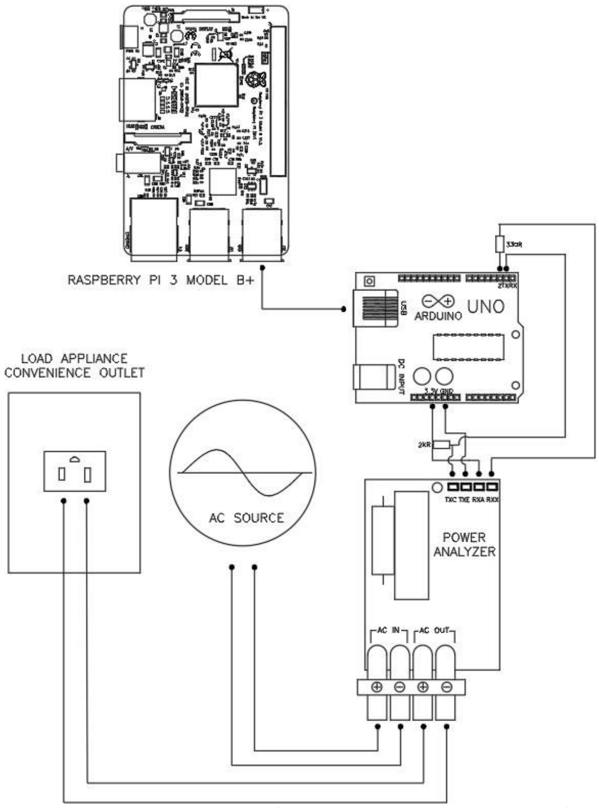

Fig. 2. Schematic diagram of the individual load monitoring of appliances.

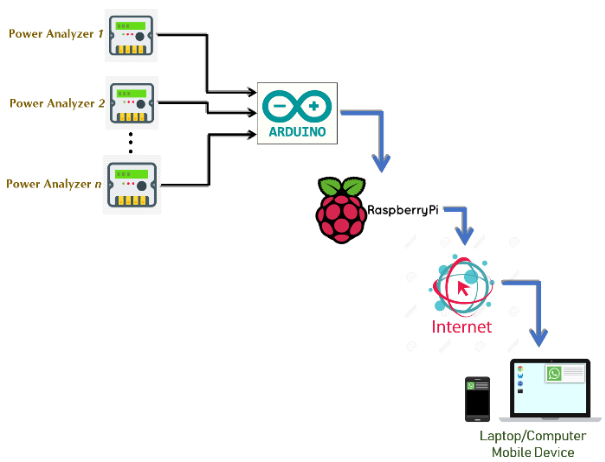

Fig. 3. Overall data flow of the energy management system.

The overall data flow is shown in Fig. 3. It starts from the power analyzer, which serves as a sensor to read the energy consumption of each appliances. Arduino serves as a microcontroller that supplies the direct current source of the power analyzer. Arduino sends data to Raspberry Pi for data processing of the of the energy behavior, prediction, notification and monitoring system display. All the processed data are sent to the internet by unknown broker through a web server. The data is linked from the web server to the website designated to the user where he can view using a computer, laptop or mobile phone.

On the other hand, Fig. 4 presents the whole process of how the system predicts the consumption behavior for the whole day, how it notifies the consumer of the real time energy consumption or to propose an energy saving measure, which is to reduce energy consumption.

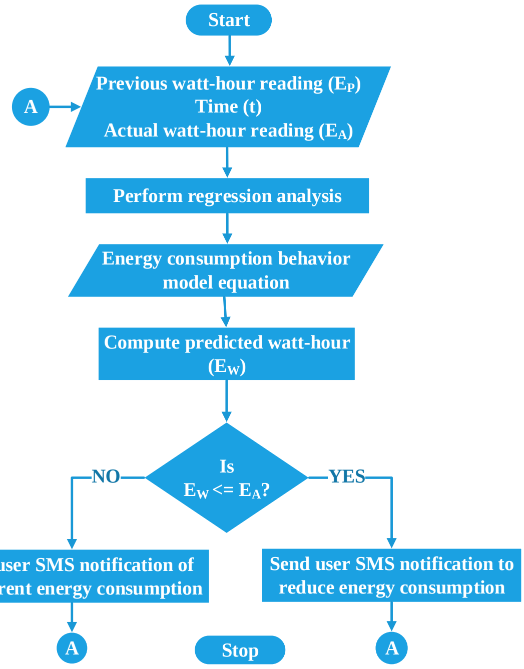

Fig. 4. Flowchart of the prediction and notification system.

Using regression analysis, input data (i.e., previous watt-hour reading (E_X), actual watt-hour reading (E_A) and time (t)) are statistically processed by the program code stored in the microprocessor. Regression analysis result, as the predicted consumption, is displayed and compared with the present-day consumption, read by power analyzer. The algorithm decides accordingly, based on how this condition is satisfied: if the current day consumption (E_A) is equal or less than the energy consumption behavior (E_Y). If E_A is less than or equal to E_Y, the system sends SMS notification to the user of his current energy consumption. Otherwise, the system sends SMS notification to the user of the proposed energy saving measure, that is, to reduce energy usage in a branch circuit.

C. *Energy Consumption Modeling*

To determine the consumption behavior, regression analysis is used. Given the consumption of the previous day as input data, the system shows the energy consumption behavior of the present day as an output. The dependent variable (Wh) and independent variable (time) are input data and the constants are calculated as the equation transforms into linear regression. There were 24 sample data obtained from the hourly energy consumption of each test appliance load. Based on the output of regression, the energy consumption behavior is modeled.

D. *Energy Monitoring System Interface*

The energy monitoring system display can be accessed by users through a website that has a log in feature or through the display dashboard of the microprocessor if internet is not available. The system has a touch screen that displays the physical meter linked to the processing system and the monitoring system of the microprocessor. The consumption power per appliance can be monitored by the user through the interface dashboard. The Node-

RED application for interface of the system was implemented. It is a flow-based programming that is suitable for internet of things (IoT) and it is a tool for wiring together hardware devices. The Node-RED provides a browser-based flow editor that makes it easy to wire together flows using a wide range of nodes in the palette. Node-Red is preferred because it is already available on the Raspbian OS in Raspberry Pi 3 microprocessor. It also has a lightweight runtime, which is ideal to run on low-cost hardware such as the Raspberry Pi microprocessor and into the cloud.

On the other hand, the SenseTecnic FRED shown in Fig. 5 is a cloud-hosted Node-RED service, designed to streamline the development of IoT applications. It also uses the same principle of node flowing and a cloud database. The SenseTecnic FRED gets the data on the database via MQTT through an unidentified broker that can be accessed through a right and specific topic.

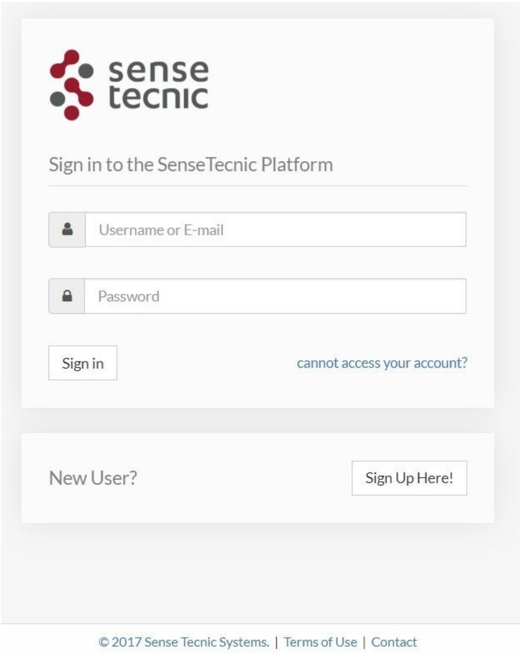

Fig. 5. SenseTecnic FRED sign in platform [21].

E. Tests and Statistical Treatment of Data

Prediction accuracy test and notification system accuracy test were conducted on the prototype. Statistical treatment was implemented on the test data, except for the test on notification accuracy. An additional test was done to determine the power consumption of the whole setup.

Prediction accuracy test shows how close the predicted consumption (energy consumption behavior) is to the actual consumption for a day. Each branch of the circuit had an electric meter so it could monitor the consumption per appliance. Data read by the electric meter was the actual consumption, while the predicted consumption was the calculated value from the generated model equation. The data were treated mathematically by applying two-tailed t-test at a significance level of 0.01. It was used to test the null hypothesis that there is no significant difference between the actual consumption (Whr) and the energy consumption behavior.

The notification system accuracy test was carried out to determine the accuracy of the SMS notification system. The accuracy was measured in terms of the correctness of the notification received by the intended user according to the system logic described previously in Fig. 4. Using Microsoft Excel, the conditions whether the user should receive a notification or not were randomly generated, and those conditions were executed in the prototype for 30 trials. Results were analyzed by computing for the success rate of the samples.

On the other hand, the smart meter energy consumption was determined since the entire setup involved devices that consume electricity. It is indeed appropriate that the setup should be designed such that it will not significantly contribute to the entire household's electric consumption.

IV. Results and Discussion

A. Energy Consumption Behavior Model

This section presents the summary of the regression analysis in order to obtain the energy consumption behavior model equation of each branch. Table I represents the regression statistics for the branch with the 5-W LED lighting test load.

TABLE I: Regression Statistics of the Energy Consumption Behavior Model for Appliance Load 1

Regression Statistics				
Multiple R		0.97050		
R Square		0.94190		
Adjusted R Square		0.93930		
Standard Error		0.02200		
Observations		24.0000		
	Coefficients	Standard Error	t Stat	P-value
Intercept	-0.035913	0.0093	-3.8720	0.0008
X Variable 1	0.012263	0.0006	18.8920	0.0000

With a good fit at 94% and low standard error, the energy consumption behavior model equation is represented in (1) where y_1 is the predicted energy consumption behavior and x_1 is the number of hours since prediction period.

$$y_1=0.012263x_1-0.035913 \quad (1)$$

Table II shows the statistics of the model equation for the 5-W appliance test load which in this case was a phone charger.

TABLE II: Regression Statistics of the Energy Consumption Behavior Model for Appliance Load 2

Regression statistics				
Multiple R		0.9240		
R Square		0.8540		
Adjusted R Square		0.8470		
Standard Error		4.2250		
Observations		24.000		
	Coefficients	Standard Error	*t* Stat	*P*-value
Intercept	-1.600029	1.7801	-0.8990	0.3784
X Variable 1	1.413783	0.1246	11.3482	0.0000

The model equation, which fit is relatively good at 85% and low standard error, is represented in (2) where y_2 is the predicted energy consumption behavior of the load and x_2 is the number of hours since its prediction period.

$$y_2=1.413783x_2-1.600029 \qquad (2)$$

Another set of regression statistics is presented in Table III. It represents data of another 5-W appliance test load which was an internet modem and Wi-Fi router.

TABLE III. REGRESSION STATISTICS OF THE ENERGY CONSUMPTION BEHAVIOR MODEL FOR APPLIANCE LOAD 3

Regression Statistics				
Multiple R	0.99820			
R Square	0.99650			
Adjusted R Square	0.99630			
Standard Error	1.97420			
Observations	24.0000			
	Coefficients	Standard Error	t Stat	P-value
Intercept	-2.363822	0.8318	-2.8417	0.0095
X Variable 1	4.588269	0.0582	78.8151	0.0000

For this, the fit is good and standard error is low. Equation (3) gives the model where y_3 is the predicted energy consumption behavior of the load and x_3 is the number of hours since its prediction period.

$$y_3=4.588269x_3-2.363822 \qquad (3)$$

For the last set of regression statistics, Table IV shows the summarized data of regression statistics for the branch which variable loads were intentionally connected (e.g., 40-W laptop charger and 50-W electric fan). This branch was purposely tested for variable loads to show how the system will predict the behavior.

TABLE IV: REGRESSION STATISTICS OF THE ENERGY CONSUMPTION BEHAVIOR MODEL FOR APPLIANCE LOAD 4

Regression Statistics				
Multiple R	0.92250			
R Square	0.85090			
Adjusted R Square	0.84410			
Standard Error	60.9616			
Observations	24.0000			
	Coefficients	Standard Error	t Stat	P-value
Intercept	-77.238072	25.6862	-3.0070	0.0065
X Variable 1	20.144459	1.79770	11.2059	0.0000

It can be noted that standard error is quiet high for this model (4) where y_4 is the predicted energy consumption behavior and x_4 is the number of hours since its prediction period. Varying loads may have contributed to this. Nevertheless, the fit is still relatively good.

$$y_4=20.144459x_4-77.238072 \qquad (4)$$

B. *Prediction Accuracy Test Results*

Fig. 6 and Fig. 7 represent sample data gathered from the branch where 5-W appliance load (internet modem and Wi-Fi router) was connected for this test, as well as data from another branch of variable loads (e.g., 40-W laptop charger and 50-W electric fan).

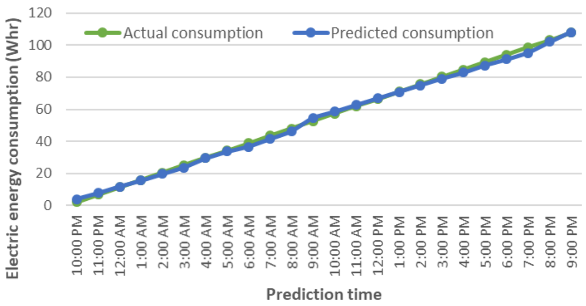

Fig. 6. Actual and predicted energy consumption of branch with 5-W appliance load.

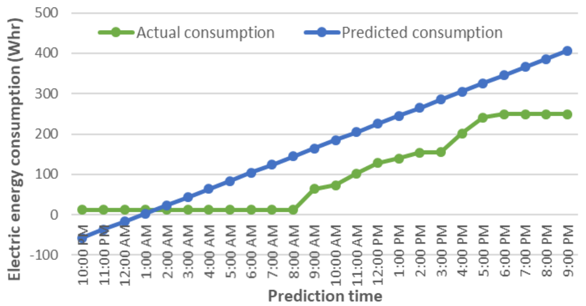

Fig. 7. Actual and predicted energy consumption of branch with variable load.

TABLE V: TWO-TAILED T-TEST RESULTS OF THE BRANCH WITH 5-W APPLIANCE LOAD

Parameter	Variable 1	Variable 2
Mean	54.98954096	54.35358333
Variance	1052.610685	1016.760148
Observations	24	24
Pooled Variance	1034.685416	
Hypothesized Mean Difference	0	
df	46	
t Stat	0.068488024	
P(T<=t) one-tail	0.472847	
t Critical one-tail	2.410188096	
P(T<=t) two-tail	0.945694	
t Critical two-tail	2.763262455	

TABLE VI: TWO-TAILED T-TEST RESULTS OF THE BRANCH WITH VARIABLE LOADS

Parameter	Variable 1	Variable 2
Mean	99.55129167	174.5676333
Variance	9327.862328	20289.95555
Observations	24	24
Pooled Variance	14808.90894	
Hypothesized Mean Difference	0	
df	46	
t Stat	-2.135428196	
P(T<=t) one-tail	0.019041508	
t Critical one-tail	2.410188096	
P(T<=t) two-tail	0.038083017	
t Critical two-tail	2.687013492	

In Table V, results when data of the 5-W load were subjected to two-tailed t-test were presented. It can be clearly seen that t Stat is less than t Critical two-tail, suggesting that there is no significant difference between data sets. Thus, it can be said that the predicted energy consumption is 99% accurate compared with the actual energy consumption.

On the other hand, t-test results for the variable load data were shown in Table VI. Variance may be large, but, t Stat is still less than t Critical two-tail. It only suggests that even for varying loads, the regression analysis-predicted energy consumption is 99% accurate compared with the actual energy consumption.

C. Notification System Accuracy Test Results

As described previously in Fig. 4, if the predicted energy consumption behavior equals or exceeds the actual consumption, the system would send an SMS that would notify the user to reduce energy usage in the branch circuit. This function was tested under notification system accuracy test.

Out of 30 randomized conditions in each set of tests (a total of four separate tests), the system either sent successful notification alert or did not send any notification alert to users as needed, in every trial of the test. In other words, the system showed 100% success in performing the intended action according to the predefined condition. A sample notification sent to and received by user is shown in Fig. 8.

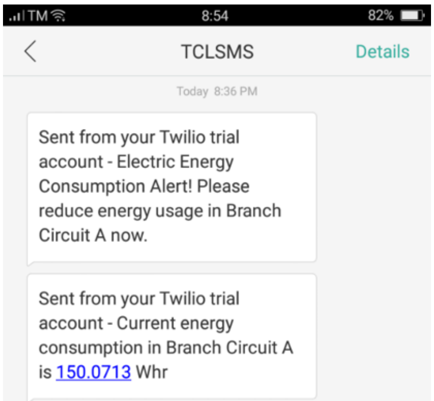

Fig. 8. Energy consumption notification alert when predicted consumption is less than or equal to actual consumption.

D. Smart Meter Energy Consumption

The system was run continuously for 30 minutes in 15 sets of trial. The average energy consumption is recorded at 2.298 Whr. In an hour, 4.596 Whr will be consumed and in 24 hours of operation, a consumption of 110.304 Whr will be expended. This figure, when further translated into its equivalent electric bill in a 30-day period, with Meralco rate for May 2019 as PHP10.29 per kilowatt hour [22], will amount to only PHP34.051. This amount brings indeed a minimal impact to a typical household consumption. Thus, the system will not significantly contribute to the entire household electric energy consumption.

V. Conclusion

Being able to monitor each household appliance would make it easier to identify which load consumes more energy. Being able to identify the consumption behavior of each load gives every household opportunity to save energy or at least reduce its usage. In order to do this, an intelligent home energy management system must be in place. It requires accurate load monitoring system to optimize system functionality and this is where intrusive method of load monitoring comes in.

This project successfully created an energy management system for household applications that employed intrusive method of load monitoring and wireless network technology in data transmission to access this system. Another feature of the energy management system that was developed is the energy consumption behavior model used in providing energy saving notification.

Wireless transmission of smart meter data was successfully carried out through utilization of Wi- Fi-ready Raspberry Pi 3B+ and SenseTecnic cloud host. The notification system was accomplished through another cloud-based communication platform, the Twilio and it is 100% successful in sending notification to the user of the proposed energy saving measure, that is, to reduce energy consumption in the branch circuit.

As for the energy consumption behavior, regression analysis produced model equation for each specific type of appliance load used in this project. Equations have relatively good fit, with R squared of 85% - 94%, and low standard error, except for the branch with varying loads and sporadic consumption pattern. Nevertheless, there is 99% confidence in the accuracy of the energy consumption behavior as demonstrated in the prediction accuracy test result. Thus, it validates the applicability of the energy consumption behavior model equation.

The entire smart meter's electric consumption cost, PHP34.051 for a 30-day operation does not contribute significantly to a typical household electric energy consumption.

This study relies on the energy consumption and consumption prediction per appliance in the household. For a more precise and accurate prediction, other regression analysis, such as nonlinear regression or multiple regression, and machine learning can be performed.

The whole system involves complex arithmetic and logic operations. The use of mathematical application for processing microprocessor is highly recommend.

This home energy management system has a monitoring and energy saving feature that will inform the user of his energy consumption and energy saving measure. However, saving is unrealized unless the suggested method to reduce consumption is executed by the user or actuated electrically. Hence, the latter is put forward as an area for improvement.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Maria Criselda B. Loyola is the research adviser who conceptualized the topic, worked on the statistical part and data analysis, and reviewed and edited the full manuscript and all its content. Jeremiah O. Joson worked on writing several sections of the full manuscript as well as in the coding/software part of the prototype model. Lance Bryan D. Salvador wrote the remaining sections of the full manuscript and at the same time, worked on the hardware part of the prototype. All authors had approved the final version.

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