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A new smart approach of an efficient energy consumption management by using a machine-learning technique

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ABSTRACT

Many consumers of electric power have excesses in their electric power consumptions that exceed the permissible limit by the electrical power distribution stations, and then we proposed a validation approach that works intelligently by applying machine learning (ML) technology to teach electrical consumers how to properly consume without wasting energy expended. The validation approach is one of a large combination of intelligent processes related to energy consumption which is called the efficient energy consumption management (EECM) approaches, and it connected with the internet of things (IoT) technology to be linked to Google Firebase Cloud where a utility center used to check whether the consumption of the efficient energy is satisfied. It divides the measured data for actual power (A_p) of the electrical model into two portions: the training portion is selected for different maximum actual powers, and the validation portion is determined based on the minimum output power consumption and then used for comparison with the actual required input power. Simulation results show the energy expenditure problem can be solved with good accuracy in energy consumption by reducing the maximum rate (A_p) in a given time (24) hours for a single house, as well as electricity's bill cost, is reduced.

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1. INTRODUCTION

The most recent research that deals with the energy consumption from the electricity consumers which are saved in different ways to reduce the maximum rate of energy consumption through specific times, many processes that be done to satisfy the useful or efficient energy consumption of these processes are called energy management. This management can be connected with machine learning (ML) and many works are dealt with it [1]-[3]. The research [4] presented a hybrid machine learning approach that includes both unsupervised and supervised categorization. Consumers are classified depending on how similar their normal electricity use routines are. To extract common electricity usage behaviors, an unsupervised clustering approach is applied. A fuzzy ranking system for consumers, followed by a novel algorithm to select great products. Consumer types and their preferences in terms of consumption. The algorithm for supervised classification is used to categorize new customers and analyze the health of specific groups of people. The proposed model is tested using real data from non-US users obtained through smart meters for a year and a half. The findings showed that large or exceptional institutions have differently valued, although medium and small entities, as well as similar building styles, may have the same features.

Montañez and Hurst [5] presented a machine learning comparison of unemployment prediction for single home residents using derived features from smart meter electricity measurements. A variety of nonlinear classifiers were evaluated and compared. The results are compared to a generalized linear model. To ensure the works' long-term viability, they employed cross-validation regularly. The findings demonstrated that the employment condition may be predicted. Using an area under the curve (AUC) of 74%, sensitivity (SE) of 54%, and specificity (SP) of 83 percent. A multilayer neural network with leakage followed by distance results with a polynomial kernel model and weighted discrimination was adopted. The enhanced and distributed internet of things (IoT) technology network was also utilized to gather data.

In addition, the researchers of [6]-[8] aimed to examine recent studies on energy consumption modeling and estimation in various areas. Governments can use their works to implement energy-saving programs, for example, machine learning algorithms can estimate how much energy is consumed in a house and it may also be used to estimate the future use of other sources of energy, such as electricity or natural gas. These studies were based on the prediction of various energy types.

Yang *et al*. [9] proposed an energy estimation approach that uses the architecture, parallelization, and bit-width of a deep neural network (DNN) to estimate its energy consumption. This approach can be used to test and direct the design of energy-efficient DNNs by evaluating the various DNN architectures and energy-efficient techniques that are currently being proposed in the field. A further work [10] proposed IoT data collection and analysis; they suggest an energy-efficient approach; first, before transmission, they apply a fast error-bounded loss compressor to the collected data, which is considered the most energy-intensive component in an IoT system. They reconstructed the transmitted data on an edge node in the second step and process it using supervised deep learning techniques. To substantiate their approach they use the context of driving behavior monitoring in intelligent drive systems to verify their approach, in which blood tests data is collected from the driver through a wireless body sensor network (WBSN) and wearable devices and sent to an edge node for different stress tracking.

All of these related research works face challenges to work with or are not easy to understand, moreover, they are not new works, and they are not mentioning how to satisfy the efficiency of energy consumption without energy theft in their works even they use a well-known ML technique. In this work, we use a new simplest one of the ML techniques, it differs from the previous methods presented above, we find the efficient energy consumption data by detecting cases of theft that occur by some hackers of electrical power transferred who have been supplied with quantities of electrical energy more than what is planned by electrical power distribution circuits. The validation approach proposed as one approach of the efficient energy consumption management (EECM) processes which have two types of data (approaches) that it can be found in two ways; the first way is the traditional way, where the energy consumption data with the amount of energy expenditure that must measure normally and periodically for one house every 24 hours by using the traditional energy metering and then writing these un-useful data. The second way is newer and smarter using the validation approach where the ML is involved to find the efficient energy consumption smartly to find the useful result data (data without the amount of energy expenditure in it) [11]. EECM can be built with large combination methods that are operated smartly with the precision and usefulness of the smarter method.

2. PROPOSED PROCEDURE

In our work, we proposed the validation approach as one approach of the EECM approaches to solving the problem of exceeding energy consumption and energy theft by specifying the higher active power $(\mathrm{A_p})$ for energy consumption, our proposed solution is one of the AI branches of the smartest ML technology, where the problem arises from learning how to spend energy productively. As a result, the validation strategy is simulated and executed in the MATLAB program. We proposed using $(\mathrm{A_p})$ as an estimated active power to overcome the issue of higher energy consumption $(\mathrm{E_c})$, where the problem comes due to a limited and useful way of energy-consuming. Then, by reducing the $(\mathrm{A_p})$, we improve Ec's performance and to see what effect it had on $(\mathrm{E_c})$'s behavior, and we see what happened to the $(\mathrm{E_c})$'s a cost in terms of energy consumption as the $(\mathrm{A_p})$ decreased. As a result, $(\mathrm{A_p})$ compares the traditional and estimated values to determine the difference in the $(\mathrm{E_c})$ output values. To describe the $(\mathrm{A_p})$ Methods, we need first to know the electrical energy model and the mathematical model's types for our proposed solution.

2.1. Electrical energy model

Energy is described as the ability to perform work overtime period, people (the electrical consumers) have learned how to convert energy from one type to another and then use it to do work, making modern society possible. There are several different types of energy sources, which can be classified into two types: renewable and nonrenewable [12]. Renewable and nonrenewable energy sources may use to generate primary energy such as heat, or secondary energy such as electrical and hydrogen energies [13], [14]. In our work, we take electrical energy as a case study which has two main categories: active and reactive powers, and we consider the active power as the actual power transmitted to electrical devices such as electric appliances, lighters, and heaters, and then the consumed electrical energy can be found by multiplying the active power (A_p) by the time taken to consume electrical energy (E) as in (1):

$$E = A_p \times T \quad (1)$$

where (A_p) has represented the actual power measured in kilowatts (kW) and (T) is represented time measured in hours [15]. The term energy efficiency [11], [12] refers to the ability can save the amount of useful energy consumed by industrial equipment and distribution in comparison to the total of input energy generated, the link between energy consumers and the energy consumption is the client-utility center, which is responsible for finding the efficient energy consumption in a real-time by measured the energy-consuming that specified by the parameters which influence on the overall energy consumption, the main formula of the energy efficiency is a percentage ratio between useful consumption energy to total input energy as in (2):

$$EE\ \% = \left(\frac{E_c}{E_i}\right) \times 100\% \quad (2)$$

where (EE) is energy efficiency, (E_c) is the energy consumed by consumers and (E_i) is energy input [16], [17].

The energy input is represented how much energy reached the consumers from the government, which may behave equal quantities reached them according to its government and energy output, every ministry of electricity in the world provides its consumers with a certain amount of energy that differs from its counterparts in other countries. These measurements were made in the State of Iraq, where the consumer is provided with a quantity of electrical energy 53 (kilowatt-hours) that the citizen must comply with without exceeding it to obtain (E_c) is useful, and vice versa. Exceeding the permissible limit consumes electrical energy, and it is warned that the power will be cut off from it if the permissible amount does not normalize the electric current, therefore; the (E_c) must be useful energy if all consumers consume with caution to satisfy the energy efficiency formula with the best result. For that, we need to define the scale, which used to measure the efficiency of the energy consumption that standard, called the power factor $\left(P_f\right)$ [18] for the active power $\left(A_p\right)$. We need to know the actual power transmitted to nonlinear loads [19]-[21], such as electric appliances, lighters, heaters, and laptops (kW); therefore, to calculate it we must first learn that the current (I) lagging by 90 degrees behind the voltage (V) by an angle for the electrical loads that be used in our houses, the vector diagram which is being used to describe currents and voltages that are perfectly sinusoidal signals. The current vector can be divided into two components in this vector diagram: one in phase with the voltage vector (component I_a) and the second is lagging 90 degrees (component I_r) [2] usually the power factor $\left(P_f\right)$ is given in (3):

$$P_f = cos\varphi \quad (3)$$

After that, the (A_p) can be described by the following expression:

$$A_p = \mathrm{V} \times I_a = \mathrm{V} \times \mathrm{I} \times P_f = \mathrm{V} \times \mathrm{I} \times cos\varphi \quad (4)$$

Now, we need to define a new term namely period of consumption (POC) which represents the range between ending time and beginning time in hours for the consumption of different devices type. In our research to find an appropriate and effective energy consumption mathematical model, we must first determine the type of electrical nonlinear loads, we assumed two different examples to evaluate the parameters of the energy consumption of our suggested system, we assumed a collection of devices in each smart house, for satisfied the proposed EECM, we divided our devices into two groups (group x and group y). The devices of the group (x) are the device used continuously D_x is given in (6), and the devices were located in the group (y) are the devices not used continuously D_y is given in (7); therefore, the type of the total device is given in (5):

$$A_p = \mathrm{V} \times I_a = \mathrm{V} \times \mathrm{I} \times P_f = \mathrm{V} \times \mathrm{I} \times cos\varphi \quad (5)$$

$$D_x = d_x 1 + d_x 2 + d_x 3, \ldots\ldots, d_x i \quad (6)$$

where i is the number of devices used continuously.

$$D_y = d_y1 + d_y2 + d_y3, \ldots\ldots, d_yj \tag{7}$$

where j the number of devices not used continuously.

We assumed four various devices in one house in this research. The (A_p) consumption (kW) will be in a low active if one device is operated or highly active if all devices are operating. Table 1 shows the actual power consumption measurement for all four devices through 24 hours/day to register the active power for each device exactly.

Table 1. Actual power consumption measurement

Device type	Device name	Device number	(A_p) consumption (kW) low active	(A_p) consumption (kW) high active	start Time (h)	End Time (h)	POC (h)
Group X	Interior Lighting	5	0.06	0.3	01	24	24
Group X	Fridge	2	0.3	0.6	01	24	24
Group Y	Air Condition	5	1.2	6	01	24	24
Group Y	Washing Machine	2	1	2	01	24	24

In addition, the cost of the energy consumption in every house is calculated according to how much active power is measured through one hour for the nonlinear loads so below putting a table used to specify the cost of the energy consumption divided into six units according to the E_c (kWh) which are determined by the ministry of electricity in Iraq. The (E_c) is the energy consumption for devices are consumed by the consumers and $C(E)$ is the total price of the energy consumption for devices consumed through one hour by the energy consumers as shown in Table 2.

Table 2. The energy consumption unit cost

Unit name $U(C(E))$	E_c (kWh)	$(C(E))$ (\$)
A	0.1-1	0.5
B	1.1 - 10	1
C	10.1 - 20	2
D	20.1 - 30	3
E	30.1 - 40	4
F	40.1 - 53	4.768

2.2. Mathematical model analysis

There are two types of mathematical models according to the electrical nonlinear load's type which is represented by the number of hours of continuous or intermittent consumption of the electrical device, group x, and group y, to find the final formula of the output data for our proposed EECM process, we do the following analysis:

2.2.1. Mathematical model (group X) devices

Fixed load devices are another name for this type of device. This means that switching on from one time to another, interrupting the work of such devices is not essential, or it is used for approximately a fixed number of hours per day. Used continuously devices need a limited time to complete their working start time. This group includes interior lighting and fridges. The mathematical models' devices of group x for the actual power consumption is given in (8):

$$A_{px} = V_x \times I_x \times P_f = V_x \times I_x \times cos\varphi \tag{8}$$

where (A_{px}) has represented the actual power measured (kW), (V_x) is the voltage (V) and (I_x) the current in group x. The total energy consumption is calculated for one day through 24 hours for one house by using (9):

$$E_c(x) = \sum_{T=1}^{24} \left(A_{px} \times d_x(T)\right) \tag{9}$$

where the parameters of this group are: $(E_c(x))$ is the energy-consuming for the device used continuously, $d_x(T)$ is the device used for each device that is active in one time (T), D_x and all devices are used continuously. After that, we can calculate the total cost of consumed energy for devices used continuously. $C\left(E_c(x)\right)$ for one house through 24 hours by using the following formula is given in (10):

$$C\left(E_c(x)\right) = U\left(C(E)\right) \times \rho(\mathrm{T}) \tag{10}$$

where $C(E)$ is the cost of the energy consumption for each device used continuously.

We can be using data as shown in Table 2 to know any unit type of energy consumption $U(C(E))$, and we can use this expression according to $E_c(x)$, ρ(T) represented if the device used in the house is on, it is equal to one or if the device used in the house is off, it is equal to zero through period (T) hours.

2.2.2. Mathematical model (group Y) devices

Devices not used continuously are manual shifter devices that can be switched to any prime time within 24 hours. It is also possible to stop these devices from working. Here is where we bring the air condition, washing machine, coffee machine, scanner, microwave oven, tablet, vacuum cleaner, electric car, iron, washer, and hairdryer. The mathematical models' devices of group y for the actual power consumption is given in (11):

$$A_{py} = V_y \times I_y \times P_f = V_y \times I_y \times cos\varphi \quad (11)$$

where (A_{py}) has represented the actual power measured (kW), (V_y) is the voltage (V) and (I_y) the current in group y.

The total energy consumption is calculated for one day through 24 hours for one house by using the following formula given in (12):

$$E_c(y) = \sum_{T=1}^{24} \left(A_{py} \times d_y(T)\right) \quad (12)$$

where the parameters of this group are: $E_c(y)$ is energy-consuming for devices not used continuously, $d_y(T)$ is the device not used for each device is active in one time (T) and D_y are all devices not used continuously, after that, we can calculate the total cost of consumed energy for devices not used continuously $C\big(E_c(y)\big)$for one house by using the following formula is given in (13):

$$C\big(E_c(y)\big) = U\big(C(E)\big) \times \rho(\mathrm{T}) \quad (13)$$

where $C(E)$ is the price of the energy consumption for each device not used continuously, we can be using Table 2 to know any unit type of energy consumption $U\big(C(E)\big)$ we can use this equation according to $E_c(y)$, $\rho(T)$ represented if the device used in the house is on equal one or off to equal zero through period (T) hours. Finally, by using the upper equations, we can find the final formula of the total energy consumption for one house in all types of devices is given in (14):

$$E_c = E_c(x) + E_c(y) \quad (14)$$

where (Ec) is the total energy consumption.

The total efficient energy consumption (EE_c) is given in (15):

$$EE_c\% = \left(\frac{E_c(x)+E_c(y)}{E_i}\right) \times 100\ \% \quad (15)$$

The total prices for energy consumption $C(E)$ is given in (16):

$$C(E) = C(E_c(x)) + C(E_c(y)) \quad (17)$$

Moreover, the total prices for efficient energy consumption $C(EE)$ are given in (17):

$$C(EE)\% = \left(\frac{C\big(E_c(x)\big)+C\big(E_c(y)\big)}{C(E_i)}\right) \times 100\ \% \quad (17)$$

where $C(E_i)$ is the total price for input energy consumption, it is depending on how much the input energy consumption equals.

3. RESEARCH METHODOLOGY

We have two approaches of the EECM processes for calculating the (A_p) consumption including the traditional approach and the validation approach for calculating the electrical energy consumption. These two approaches are tested and verified by using the estimated and measured data for one day per different times for one house. The following sections describe how these two approaches are worked.

3.1. Traditional approach

This approach faces the problem of exceeding energy consumption and theft, especially in the summer season by using ordinary electric meters [3] in one house. If we assume that the type of all devices is active and the current input is assumed to equal 10 Ampere and the input voltage is equal to 220 volts, so the (A_p) consumption is equal to 2200 watts; therefore, the total input energy is $E_i = 53\ kwh$ through 24 hours for one day in one house with $C(E_i)$= 4.768 $, then by using the mathematical formula in the above expressions, we calculated every parameter for one assumed house through different time (h) for one day in one house, the (A_p) consumption (kW) which is measured by using the electric meter, we can use the MATLAB program to calculate the output data, we can calculate the total energy consumption (E_c) for devices of the group (x) and the group (y) through specific time (hours) by using the traditional approach.

3.2. Validation approach

To find a new method of our proposed model for electrical energy consumption to solve the exceeding energy consumption and theft problem, we used one of the famous machine learning (ML) methods, namely the validation approach [22]-[24]. The validation is an approach that was previously used by the AI community, but here in our research the validation approach has been formulated again with a radical change in the basics of its work with comprehensive change in the contents and basics of its work, this approach is connecting with the internet of thing (IoT) smart technology over a Wi-Fi network to save the management's data in the Google Firebase Cloud to become smart treatment one approach for the An efficient energy consumption management (EECM) approaches. So as the utility center is often checking whether the efficient energy consumption is satisfactory and without any theft or wrong energy expenditure. The validation approach used to find and learn a new electrical model for the A_p and the input data T. The validation approach aims to satisfy efficient energy consumption which means the output results (E_c) must be without the amount of energy expenditure; therefore; if the efficient energy is satisfied, then the validation approach is finished else if the energy consumption data is choosing the different training data, the difference between the training data and the input data is the key because no validation approach can achieve the desired goal with invalid estimation data. This process is known as "generalization" [25]-[27]; however, it can occasionally lead to "overfitting" [28]-[30] which is caused by corruption of the generalizable data (output result with the amount of energy expenditure), lowered performance, and caused invalidity of the generalization process so we propose a solution for this problem in our approach. The validation contained some points to satisfy a good performance for the electrical model which has output results with the amount of energy expenditure. The work procedure for the validation approach describes in the following points:

i) Firstly, we must divide our actual measured power data into groups for a specific time as follows:
   a) The first group is "the training portion" which is chosen depending on the maximum actual measured power means choosing old input and output data with and without the amount of energy expenditure and it must be different from the input actual measured power data which means data with the amount of energy expenditure.
   b) The second group is "the validation portion" which is represented as the minimum rate of the E_c of the actual measured power as useful energy consumption (output result data without the amount of energy expenditure).
ii) Secondly, the ratio of actual power measurement to energy consumption output is proposed to be at ratio 9:3 because we suppose the training portion at (75%) from the training data as the training input to the ML and we suppose the validation portion at (25%) from the training data to make their data smartly as useful measured for actual power with a specific time or "the useful energy consumption output" which means the lowered energy consumption that used by the consumers.
iii) The data in the validation portion is used just for tracking and evaluating a good performance for our electrical energy model according to the following metrics:
   a) If the output data have overfitting less than or equal to 10% then the energy consumption output is useful for consumers, complete the validation approach.
   b) If not that is meaning there is overfitting in our generalization process and we must update the training data and go back to step 1.

The two portions of the validation approach can be shown in Figure 1 and the flowchart of the validation approach procedure is shown in Figure 2. After updating the training process until the output data have the energy expenditure less than or equal to 10% then the energy consumption output is useful for consumers and the validation approach is complete. So, we got a new use for A_p consumption (kW) which is measured in all seasons of one year by using the electric smart meter, and we have new output results (E_c (KWh)) with a limited exceeding of the energy expenditure to less than or equal to 10%.

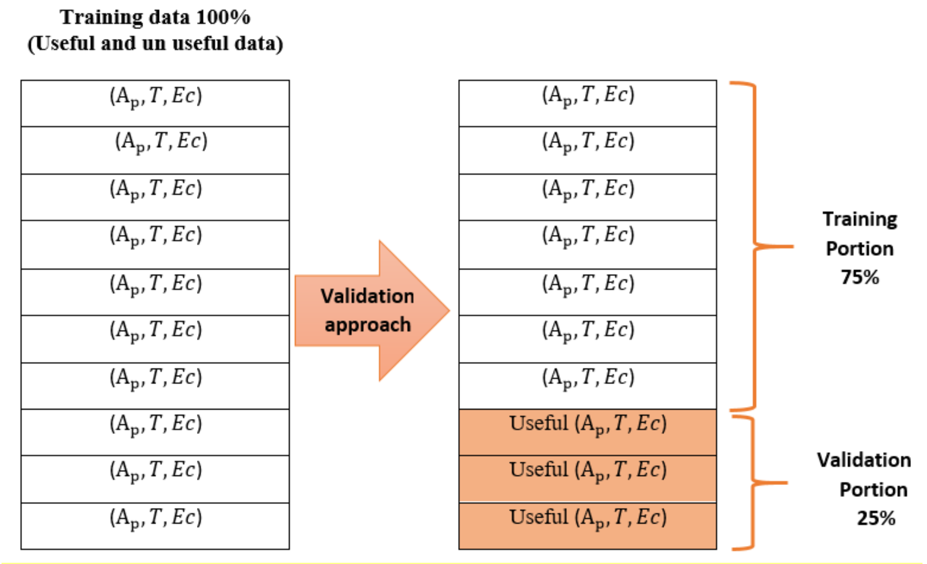

Figure 1. Validation approach

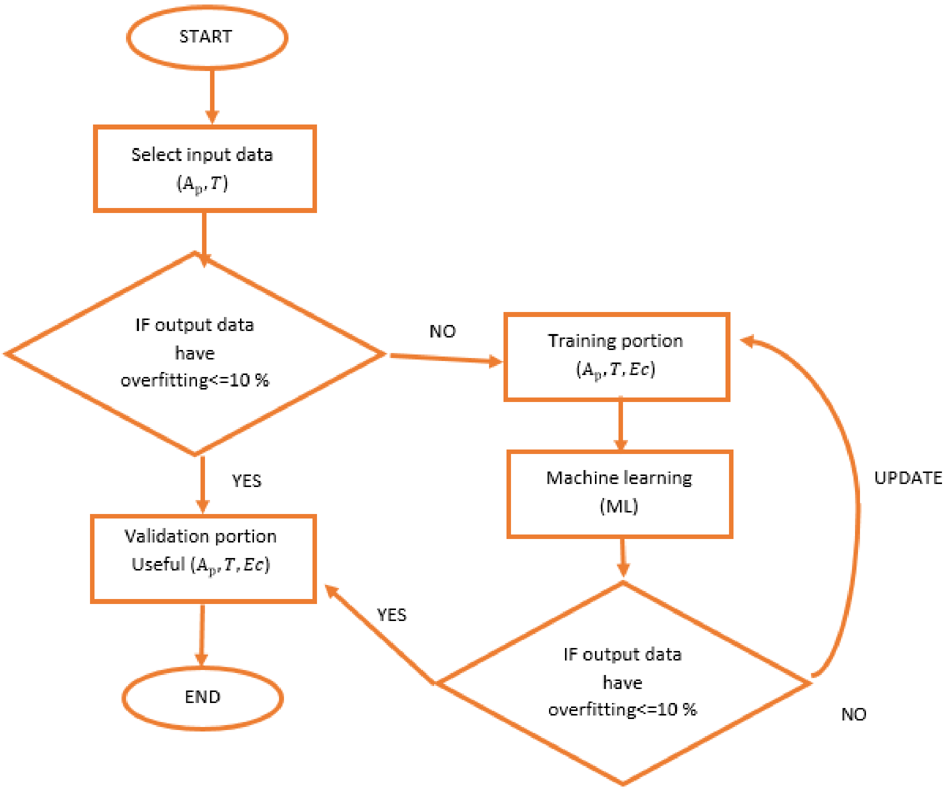

Figure 2. The flowchart of the validation approach

4. RESULTS AND DISCUSSION

Our simulation work does use the MATLAB program to represent the calculations of the output data by using the above-derived expressions. Simulation results show the difference between the output data of the traditional approach and the output data of the validation approach for the estimations and measured actual power demand in one day through the different time (hours) in one house, we noted the (A_p) with specific time is the heart of our electrical model in both approaches, this is especially helpful if the description is used in the validation portion to estimate nonlinear loads in our houses that are especially resistant to variation in the rounding of the energy consumption by the electrical consumers, the validation approach is satisfied the important aim which is how to reduce (A_p) by learning how to use it suitably as shown in Figure 3. So, we noted that the devices of the group (x) have a maximum rate of the (E_{cx}) /(KWh) through the times (06, 08, 10, 12, 14, 16, 18) hours by using the traditional approach and the ($A_{px} = 2.5KW$) and a maximum rate of the (E_{cx})/(KWh) through the times (06, 08, 10, 12) hours by using the validation approach the ($A_{px} = 1.5KW$), also we noted the devices of the group (y) have a maximum rate of the (E_{cy})/(KWh) through the times (12, 14, 16) hours the ($A_{py} = 16KW$) by using the traditional approach and ($A_{py} = 4KW$) by using the validation approach as shown in Figure 4.

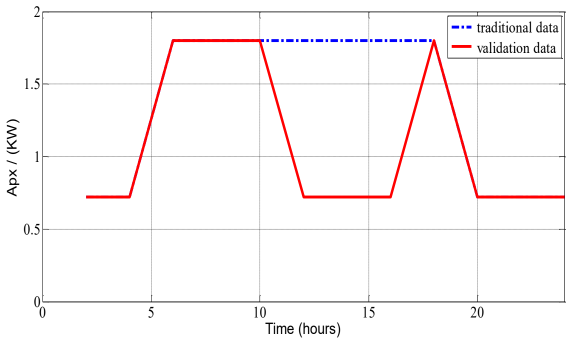

Figure 3. The total energy consumption (E_c (KWh) through time for the group x between two approaches

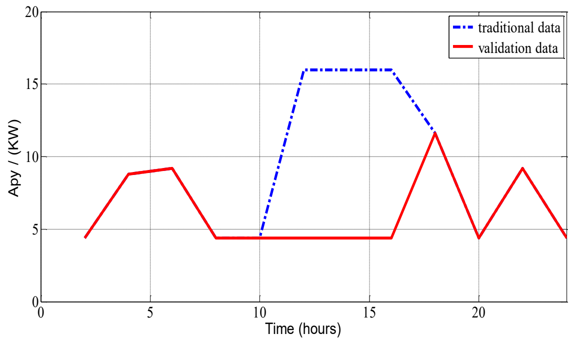

Figure 4. The total energy consumption (E_c (KWh)) through time for the group y between two approaches

Also, we noted the two devices of the two groups (x) and (y) have a maximum rate of the (E_c) (KWh)) through the specific times (12, 14, 16) hours ($A_p = 1.8KW$) by using the traditional approach by using the validation approach and ($A_p = 1.4KW$) that's mean the (A_p) is decreased in (0.4 KW) as shown in Figure 5, we noted the maximum rate of the (EE_{cx}) through the times (12, 14, 16) hours by using the traditional approach the ($E_{cx} = 0.33$ KWh) and the ($E_{cx} = 0.19$ KWh) by using the validation approach as shown in Figure 6.

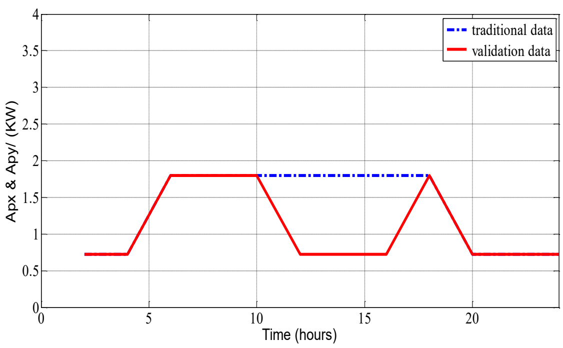

Figure 5. The total energy consumption (E_c (KWh)) through time (hours) for the group x and the group y between two approaches

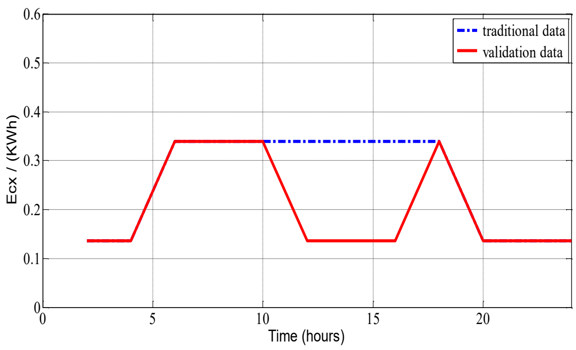

Figure 6. The difference of the total efficient energy consumption (EE_c) for the group x through specific time (hours) between two approaches

The maximum rate of the (EE_{cy}) through the times (12, 14, 16) hours the ($E_{cy} = 3$ KWh) by using the traditional approach and the ($E_{cy} = 1.8$ KWh) by using the validation approach as shown in Figure 7. The two devices of the two groups (x) and (y) have a maximum rate of the (EE_c) through the specific times (12, 14, 16) hours the $E_c = 3.4$ KWh by using a traditional approach and the ($E_c = 1$ KWh) by using the mean validation approach E_c is decreased to 2.4 KWh as shown in Figure 8. The maximum rate of the

$(C(EE_c))$ through the specific times (12, 14, 16) hours have the $(C(E_c) = 0.09\ \$)$ by using a traditional approach and the $(C(E_c) = 0.06\ \$)$ by using the validation approach that is mean the $(C(E_c)$ is decreased by 0.03\$. the (A_p) to satisfy more efficient energy consumption and there is a clear difference in energy consumption and (A_p) among different device groups for nonlinear loads in one house that fit into the same groups of the devices under the same specific time with the different measurement output data to be better and more efficient as shown in Figures 9-11.

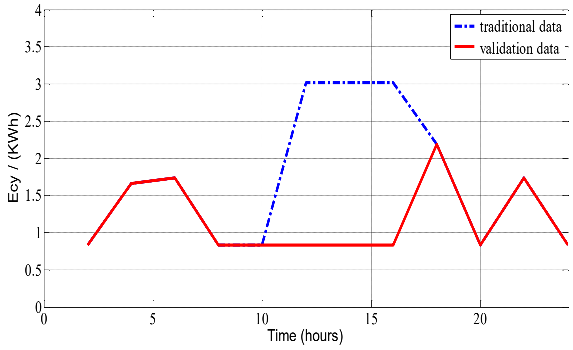

Figure 7. The difference of the total efficient energy consumption (EE_c)% for the group y through specific time (hours) between two approaches

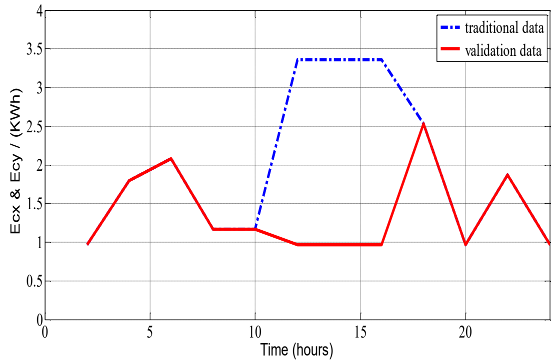

Figure 8. The difference of the total efficient energy consumption (EE_c)% for the group x and the group y through specific time (hours) between two approaches

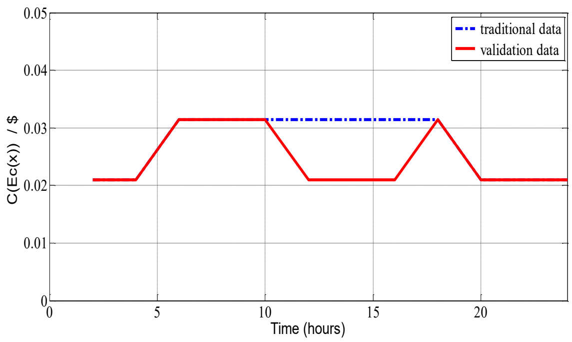

Figure 9. The total prices efficient energy consumption $C(EE)$% for the group x of two approaches

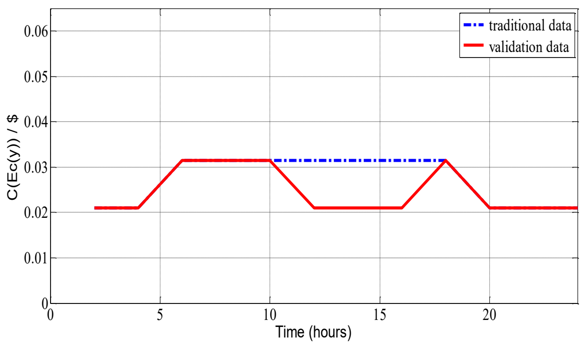

Figure 10. The total prices efficient energy consumption $C(EE)$ %for the group y of two approaches

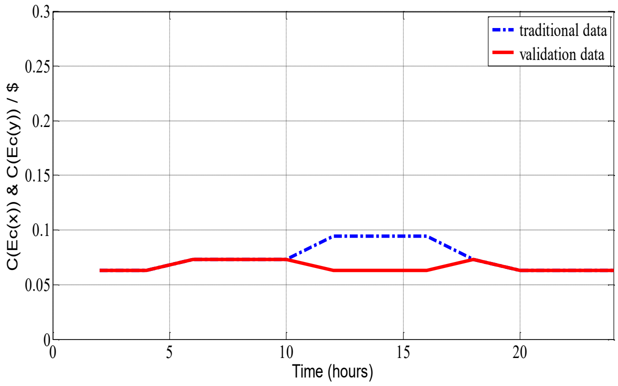

Figure 11. The total prices efficient energy consumption $C(EE)$ % for the group x and the group y between two approaches

5. CONCLUSION

Results of the mathematical modeling and power consumption are good for the devices of groups x and y, as the two models differ only in the number of times (hours) that they are run and one cannot do without the other, so the result of the two appears together, this work presented, the validation approach, which is a modern and smart method, to create more efficient energy usage for the EECM based on AI in ML techniques and it is output data (the energy consumption data in the traditional methodology with the energy consumption data in the validation approach) are compared together, we found some interesting differences between the $(\mathrm{A_p})$ and ($\mathrm{EE_c}$) data for the traditional and the validation approach. This work comes with some clear messages for us: the first approach includes descriptions with greater computational actual power, good covering for the differences in an increase during the day but with successfully accuracy, good fitting with energy expenditure, and with large overfitting for the variance in time (hours) at the day, but a validation approach provides the data that is used to track and evaluate the good performance of the electric consumers, to solve the problem of overfitting, and it is updating the training data more than once until the output data contains overfitting in the energy consumption less than or equal to 10%, the output power consumption is useful to consumers, the validation approach is completed, it means that the overfitting in the generalization process has been eliminated, and it is estimated with greater accuracy, better fitting for the variance in time (hours) at the day, therefore; we noted the $C(EE)$ is decreased when the $(\mathrm{A_p})$ is decreased then the (E_c) and the (EE_c) are decrease also which is lead to make the energy consumption is easy to become efficient with know-how estimation a good use for the (A_p) to satisfy more efficient energy consumption. Finally, we present a case study of how energy consumption estimation may be used to educate the electrical model for solving its energy expenditure problem and to make the EECM processes have stronger precision energy consumption with lower cost by reducing the maximum rate of the $(\mathrm{A_p})$ in the specific time (24) hours for one house. In the future, we could take this research in the many houses in the city, country for one, many months or years, and could increase public awareness of the importance of electrical energy to minimize the high energy consumption and learn the electric consumers how to use the energy in a true way to reach energy to all the city in a useful way without thieves of meter, hacking, and electricity theft. Additionally, will use the specification of the simulation feature in the build's tools of the google firebase cloud to simulate the implementation results instead of the MATLAB program.

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