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Prediction of electricity-consumption and residential bills based on artificial neural network

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ABSTRACT

Nowadays, predicting the value of electrical usage has made it easier for electricity consumers to reduce their residential bills. This is done by introducing a new prediction method based on the design and foundation of artificial neural network (P-EANN) technology, which is a branch of intelligent machine learning (ML) technology. The P-EANN method is based on actual data of actual power quantities that can be measured by electricity meters for the electrical model and is compared with training data that is predicted and set to the electrical usage for comparison with the reading needed to reduce residential bills. From the root mean square error (RMSE), we can find the accuracy of the residential bills ($) in the P-EANN method, which is equal to 35.69%, and the accuracy of the residential bills ($) in the standard method, which is equal to 0.00%. then the results of the MATLAB simulation for the P-EANN method enhance and reduce the residential bills from 0.5 to 4.5 dollars per day. Thus, the problem of excessive electrical usage is solved, and consumers know how to consume energy well in any place.

KEYWORDS

active power (A_p), electrical usage, residential bills, artificial neural network, standard method, prediction method

1. INTRODUCTION

Humans discovered electrical energy a long time ago and knew how to convert this energy into different forms and how to use it in different areas of our lives. Electrical energy is defined as the ability to operate continuously over a specific period of time and it comes in many forms, but its sources can easily be separated into two basic categories: natural resources and unnatural resources, both of which can be used to produce secondary electricity [1]. Many countries have rich natural resources, and they are considered an essential source of income. But the political and economic influence of countries rich in natural resources has declined as renewable energy takes a center stage in the global economy. Therefore, it can be said that these political and economic forces associated with natural resources give resource-rich countries sufficient incentive to continue using non-renewable energy [2]. To enable automated energy management in the house, home energy management systems, or HEMSs, have been presented. By transferring the load from peak to off-peak hours, HEMS lowers energy consumption while improving family convenience [3]. The load-sharing entities' DR program facilitates better active end-user cooperation.

There are two types of DR programs: cost-based and incentive-based [4]. Numerous methods for implementing HEMSs based on schedulers of load and demand-side response

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procedures have been presented by researchers. The intended outcomes are approached by a heuristic-algorithm-based mixed scheduling technique [5].

This method proposes a complicated consumer procedure: regular and unpredictable scheduling of devices. Users find this method difficult, and it is expensive to install and maintain. Using real-time tariffs, a profile-matching shift optimization algorithm [6] for residential systems for managing energy determines which loads are delayed and which are not delayed. Finding out when appliances in the house operate has an adverse influence on client service. Environmental Sustainability, the forecasting methodology is the foundation of the time-of-use pricing method. To monitor a household's energy use, this approach divides it into three states: estimation, day-ahead planning, and the correct management method [7]. False assumption numbers lead to forecast complications. Load scheduling is the foundation of the multi-objective optimization algorithm's recommended home energy management system [8]. Another strategy disregards the consequences of household energy use, which significantly contributes to environmental degradation. For the system to run smoothly, ANN-based HEMS [9] with an intelligent plug and PV production strategy are advised. The device's running times are the only factor considered by the system when planning. Home devices have a set time limit due to their dependence on the surroundings and values of their users, which might create discomfort for some users. The neural network technique offers a household energy management technique that accounts for left-on equipment. This approach considers the particular area in which the devices operate under different conditions [10]. It is challenging to formalize the device design with the proposed ANN-based approach, and the planning procedure is not clear. Users were therefore unable to use this method with every household device. The experience of the customers is reduced as a result [11]. Device planning is the basis for the HEMS proposed by the branch-and-bound approach [12] and model-based forecasting. The technique takes the processes of cost reduction and energy use into account. The qualitative and environmental implications of the customer experience are not considered by the recommended method. HVAC-type appliance scheduling is suggested by the HEMS methodology based on meta-heuristic genetic algorithm [13], which considers the tariff and operating time. As a result, not all household appliances, including those with low power consumption, may be used in the recommended manner. This method's design is difficult. A FANS-based HEMS is suggested in [14], although this strategy requires integrating renewable energy sources into the grid. A key component of a household system for energy management is the integration of renewable energy sources with the smart grid; however, demand matching weakens this strategy [15].

The article [16] analyzes medium-term estimates of power use. Regression analysis defines the challenge of predicting electricity consumption as the prior consumption of a person or group in order to use statistical or mathematical techniques to project future consumption. Finding the optimal forecasting model is the primary objective, and several approaches are taken into consideration. Neural networks and exponential smoothing are two examples of machine learning techniques. The distribution system operator in Bosnia and Herzegovina uses actual billing software to acquire monthly data on power use, which is then used to evaluate the models. R is the language used to implement and test each forecasting technique. In this article [16], the predictive method was taken within specific areas and was not considered in a general and comprehensive manner, nor did it address the extent of its accuracy in finding residential bills. The R language was used, which may have a narrow and not wide range in this field.

In our work, we proposed a new method to solve the problem of high residential bills by predicting the amount of electrical usage that the consumer must have consumed with the assistance of artificial neural network (ANN) technology. This method is called the P-EANN. The P-EANN method is proposed to schedule electrical appliances by determining the times of increased electrical usage and working to reduce it. The procedures of the P-EANN method are clear, and the type of home appliances used is not specified. It is not restricted to operating a specific type of appliance; it takes into account the cost reduction in residential bills. The main contribution of the P-EANN proposed method is to predict the desired electricity consumption and its residential bills by defining the higher active power (A_p) for the usage of electricity for all household appliances as a result of the data, then sending these data as notifications to the electricity consumers to follow these desired data. Finally, it plots these results using the MATLAB program.

2. ELECTRICAL USAGE

There are two primary kinds of electrical energy: actual and reactive powers. In our work, we defined active power as the actual power that is transferred to electrical components that humans use, such as heating devices, lighters, and other electric devices [17–19]. The amount of electrical energy used can then be calculated by multiplying active power (A_p) by the amount of time (T) it takes to consume the electrical energy (E_c) in (kWh), as shown in Eq. (1):

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

where T denotes a period measured in hours, and was the real power, measured in kilowatts (kW) [20]. The industry-standard method is used globally to measure human electricity consumption. The Ministry of Electricity determines pricing units commensurate with the individual's electrical usage, as shown in Table 1.

A value is chosen from the second column according to the amount of human consumption, determined by a value from the first column [21, 22]. For example, if the electrical usage E_c is (1.1–10) (KWh), the part of the residential bills that is calculated for this period will be an amount of one dollar after collecting the used amount of energy for a

Table 1. The energy used with its unit price

E_c (kWh)	Price (Dollar)
0.1–1	0.5
1.1–10	1
10.1–20	2
20.1–30	3
30.1–40	4
40.1–53	4.768

specific period. The final residential bill amount for this specific period has been found [20].

3. METHODOLOGY

The standard and P-EANN technique equations are explained by the methodology. The flow chart is then shown as well. It covered the use of these two strategies as well as their outcomes. subsequently, each method's RMSE and accuracy foundation.

3.1. Standard method

The standard method is the traditional method, which involves standard energy meters to periodically measure the energy-usage over the day for living houses. The data is then recorded in a single table. In one family's home, the standard method is used to determine the month-time total energy consumption. Assuming that all device types are operational and that the input voltage and current are both equal to 220 V and 10 amps, respectively, the (A_P) consumption comes to 2,200 W. Thus, for a single day in one home, E_i = 53 kWh is the total energy input over a 24-h period, with the maximum cost being the standard cost value set by the national electric station at 5 dollars. Next, without modifying the computations, the energy used is clearly explained using the equation formula Eq. (1). This method has become very old, and expensive, and it is a direct way to find the amount of energy used manually without management or the help of any modern tool [20, 23].

3.2. The proposed prediction of the electrical usage with artificial neural network method

The artificial neural network ANN has two types of layers: single-layer and multi-layer. This work examines the learning rules for artificial neural network therefore is called the P-EANN method. It has input and output layers without any hidden layers [24]. The P-EANN method uses machine learning (ML) to determine the optimal manner to use conventional electricity measurements. The training part of ML is edited out and replaced by the learning rule in ANN, which is performed in situ on any electrical model [25, 26]. However, the training data (prediction data) is analog data (any number) in order to support ML techniques [27–30]. Figure 1 shows the relationship between electrical usage and

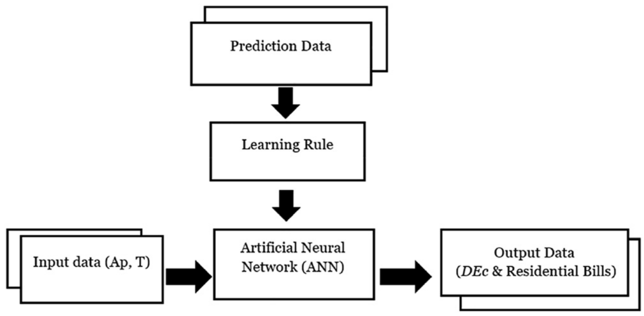

Fig. 1. Relationship between electrical usage and the ANN

the ANN. The learning rule is the process of finding the actual electrical usage rule for the artificial neural network.

In our study, we offered the Prediction of Desired Electrical Usage with its residential bills based on the Artificial Neural Network (P-EANN) method as one of the artificial neural network techniques for addressing the problem of exceeding energy usage by predicting residential bills. In this section of the project, we suggested using a neural network to predict residential bills and thus reducing electrical usage in one house for one month and have a new output result of electrical usage (KWh) with a limit not exceeding the energy expenditure of the learning rate that is less than or equal to 0.005, and that rate is used according to the process needed.

Let us suppose that the time and output layers of the ANN have signals like arrows. Every arrow of the ANN corresponds to the numbers of the signals, which are all connected with a node of the ANN. The signals correspond to the numbers of the time data (T_{IJ}) that have a position before the output nodes of the P-EANN method, and the signals correspond to the numbers of the output data for the electrical usage, respectively (E_c1, E_c2, E_c3, E_c4, … E_cI), that have a position after the output nodes of the P-EANN method. The P-EANN method has two types of nodes. The first type is like a square shape, which has the numbers of the ANN's nodes corresponding to the numbers of the input data for the active power, respectively (A_P1, A_P2, A_P3, A_P4, …, A_PJ). The second type of node is like a circle shape, which has the numbers of the ANN's nodes corresponding to the numbers of the output nodes (house nodes: House 1, House 2, House 3, House 4, House 5, …, House n) in the city where electrical usage is wanted to be checked. The ANN for the P-EANN method that receives j input data is shown in Fig. 2.

The information about the electrical usage for each house is stored in the forms of times and node IJ, which help find a suitable learning rule for the training data of the P-EANN method. The input signal of the ANN is multiplied by the time before it reaches the node IJ. The time signals are collected at the node IJ; these data are added to be the time sum. The node IJ for each house has two operations used to find the actual electrical usage.

The first operation of the node IJ has a symbol ($Æ_{IJ}$), which is called the electrical usage sum of the Prediction of Electrical usage and residential bills based on the Artificial

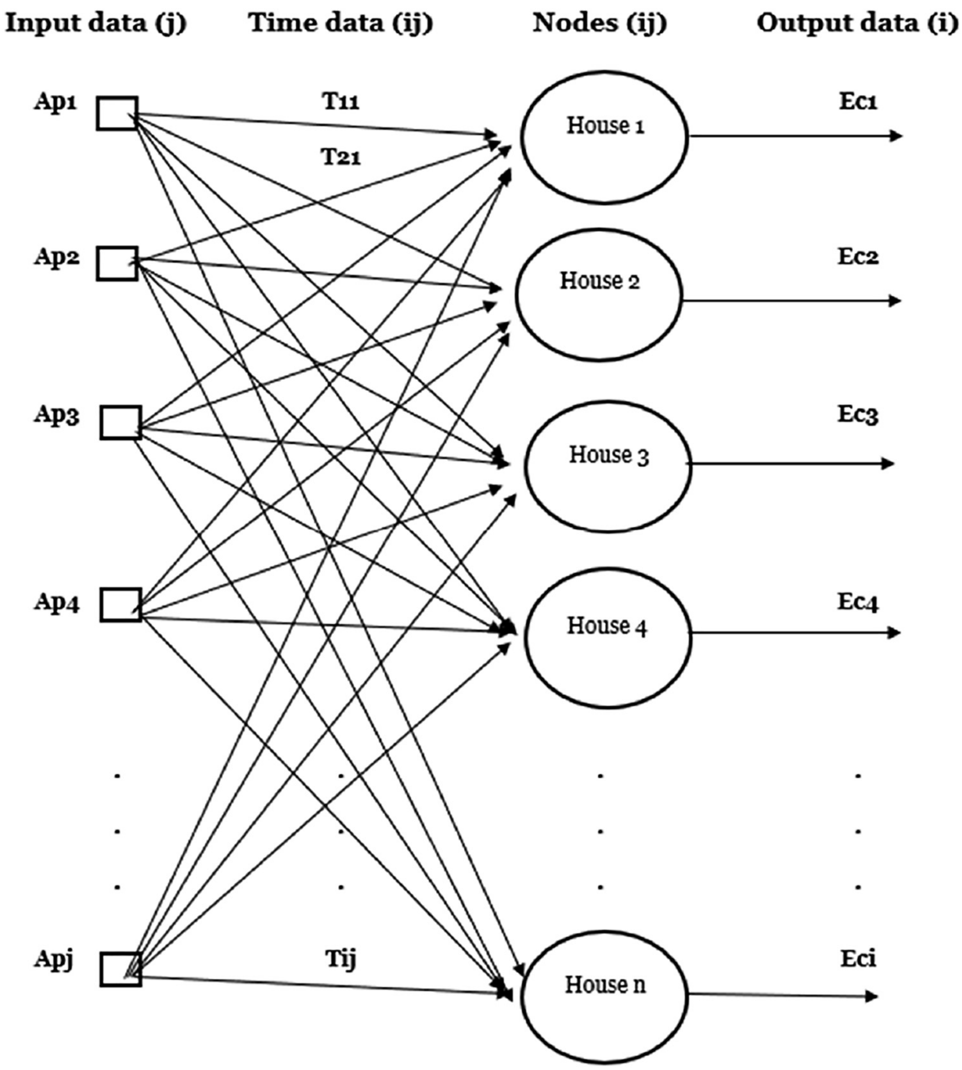

Fig. 2. The P-EANN method that receives j inputs

Neural Network (P-EANN) method because it will sum the time with the input nodes. Figure 3 shows the two operations of the node IJ (House).

The equations ($Æ_{IJ}$) of the P-EANN method for more than one house (from House 1 to House n) can be written with matrices as in Eq. (2), Eq. (3), and Eq. (4):

$$Æ_{IJ} = (T_{IJ} \times A_{PJ}) \tag{2}$$

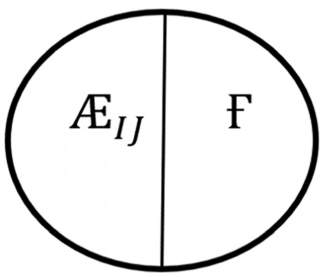

Fig. 3. Two operations of the node IJ (house)

where, T_{IJ} and A_{PJ} are respectively given by

$$T_{IJ} = \begin{bmatrix} T_{11} & T_{12} & T_{13} & T_{14} & \dots & T_{1j} \\ T_{21} & T_{22} & T_{23} & T_{24} & \dots & T_{2j} \\ T_{31} & T_{32} & T_{33} & T_{34} & \dots & T_{3j} \\ T_{41} & T_{42} & T_{43} & T_{44} & \dots & T_{4j} \\ T_{51} & T_{52} & T_{53} & T_{54} & \dots & T_{5j} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ T_{i1} & T_{i2} & T_{i3} & T_{i4} & \dots & T_{ij} \end{bmatrix} \tag{3}$$

$$A_{PJ} = \left[A_{p1}\ A_{p2}\ A_{p3} \cdots A_{pj}\right]^T \tag{4}$$

The electrical usage sum ($Æ_{1J}$) of the P-EANN method for one house is calculated in Eq. (5)

$$Æ_{1J} = (T_{11} \times A_{p1}) + (T_{12} \times A_{p2}) + (T_{13} \times A_{p3}) + (T_{14} \times A_{p4}) + \dots + (T_{1j} \times A_{pj}) \tag{5}$$

The equations of the Electrical usage sum ($Æ_{1J}$) of the P-EANN method for House1 can be written with matrices as in Eq. (6), Eq. (7), and Eq. (8):

$$Æ_{1J} = (T_{1J} \times A_{PJ}) \tag{6}$$

where, T_{1J} and A_{PJ} are respectively given by

$$T_{1J} = \left[\, T_{11}\ T_{12}\ T_{13}\ T_{14}\ T_{15} \ldots\ldots\ T_{1j} \right] \tag{7}$$

$$A_{PJ} = \left[A_{p1}\ A_{p2}\ A_{p3} \cdots A_{pj}\right]^{T} \tag{8}$$

The second operation of the node IJ has the symbol (Ƒ), which is called the useful function for electrical usage (E_{cI}) of the P-EANN method. The utility center specifies this function based on the amount of electricity that the customer uses. The second operation of the node IJ has the symbol (Ƒ), which is called the useful function for electrical usage (E_{cI}) of the P-EANN method. The utility center specifies this function based on the amount of electricity that the customer uses. Therefore, it will be used to find a useful function ($Æ_{IJ}$) to give the output data (E_{cI}) for each house. Eq. (9) gives the useful function for each House n:

$$E_{cI} = Ƒ\ (Æ_{IJ}) = Ƒ\ (T_{IJ} \times A_{PJ}) \tag{9}$$

Eq. (10) gives the useful function for the E_{c1} in House 1:

$$E_{c1} = Ƒ\ (Æ_{1J}) = Ƒ\ (T_{1J} \times A_{PJ}) \tag{10}$$

After finding the rules for each house, the learning rules will be used. The learning rule is called the actual electrical usage rule. Therefore, this method is called the prediction of electrical usage and residential bills with the artificial neural network (P-EANN) method. The actual electrical usage has a learning rule used for updating the actual power after updating the time of using it, as expressed in Eq. (11):

$$\Delta\ T_{IJ} = \Theta \times e_I \times A_{PJ} \tag{11}$$

where the ($\Delta\ T_{IJ}$) is the updating time for the node IJ, and the (Θ) is the exceeding electrical usage rate for the learning rule of the P-EANN method that has a rate between ($0 < \Theta \leq 0.005$), and (e_I) is the error ratio between the suitable output electrical usage for the users and the output electrical usage for the users as expressed in Eq. (12):

$$e_I = DE_{cI} - E_{cI} \tag{12}$$

where (DE_{cI}) is the desired output electrical usage for the energy consumers put by the electrical station.

Table 2, describes the P-EANN methodology's training data parameters, which are evaluated under a limit of 0.005, ensuring a suitable energy expenditure or DE_{cI} for optimal training data selection.

The final formula for updating the time of using it is given in Eq. (13):

$$\Delta\ T_{IJ} = \Theta \times e_I \times A_{PJ} = (0.005 \times (DE_{cI} - E_{cI}) \times A_{PJ}) \tag{13}$$

The new time equation as expressed in Eq. (14):

$$T_{IJ}(\text{new}) = T_{IJ}(\text{old}) + \Delta\ T_{IJ} \tag{14}$$

Finally, subsection Eq. (14) in Eq. (9) to get the new expression of the electrical usage in Eq. (15):

Table 2. The parameters for the training data of the P-EANN methodology

Training data (T, A_p, E_c)			
The day (in hours)	(A_p) usage (KW)	E_c (KWh)	P-EANN methodology
1	2.096	50.323	Unsuitable training data
2	0.247	5.920	Suitable training data
3	2.109	50.623	Unsuitable training data
4	0.425	10.20	Suitable training data
5	2.088	50.121	Unsuitable training data
6	1.255	30.12	Suitable training data
7	2.104	50.492	Unsuitable training data
8	1.255	30.12	Suitable training data
9	2.124	50.976	Unsuitable training data
10	0.247	5.920	Suitable training data
11	2.134	51.210	Unsuitable training data
12	0.247	5.920	Suitable training data
13	2.093	50.242	Unsuitable training data
14	0.433	10.40	Suitable training data
15	1.888	45.316	Unsuitable training data
16	1.254	30.12	Suitable training data
17	2.100	50.406	Unsuitable training data
18	1.285	30.84	Suitable training data
19	2.132	51.180	Unsuitable training data
20	1.285	30.84	Suitable training data
21	2.135	51.247	Unsuitable training data
22	2.130	51.130	Unsuitable training data
23	2.133	51.214	Unsuitable training data
24	2.104	50.492	Unsuitable training data
25	0.63	15.12	Suitable training data
26	0.63	15.12	Suitable training data
27	2.104	50.488	Unsuitable training data
28	0.63	15.12	Suitable training data
29	0.63	15.20	Suitable training data
30	2.164	51.935	Unsuitable training data

$$E_{cI} = Ƒ\ (Æ_{IJ}) = Ƒ\ (T_{IJ}(\text{new}) \times A_{PJ}) \tag{15}$$

4. SIMULATION RESULTS AND DISCUSSION

After the learning rule for the P-EANN method is compared, the error ratio between the suitable output electrical usage and the output electrical usage for the users is compared for some time until it is satisfied with the desired ratio ($\Theta \leq 0.005$), which finally means that the P-EANN method is completed and finished. It is done because it finds suitable training data for the residential bills of electrical usage. Table 1 shows the range of suitable training data for the residential bills of the electrical usage, then the output result of the suitable training data for the residential bills of the Electrical usage E_c (kWh) in the standard method and P-EANN method can be seen in Table 3. If the electrical usage of the consumers exceeds the useful learning rate specified by the P-EANN method, the electrical input data will update at the same time. A notification will be sent to the station that the scheduled data has exceeded the

Table 3. The result of the E_c (kWh) in the standard method and P-EANN method

The day (in hours)	Standard method			P-EANN method		
	(A_p) usage (KW)	E_c (KWh)	Residential bills (Dollar)	(A_p) usage (KW)	E_c (KWh)	Residential bills (Dollar)
1	2.096	50.323	5	0.247	5.920	0.5
2	2.117	50.817	5	0.433	10.40	2
3	2.109	50.623	5	0.423	10.16	4
4	2.064	49.525	5	0.425	10.20	4
5	2.088	50.121	5	0.425	10.20	4
6	2.104	50.492	5	1.255	30.12	2
7	2.104	50.492	5	1.255	30.12	0.5
8	2.104	50.492	5	1.255	30.12	2
9	2.124	50.976	5	0.86	20.64	0.5
10	2.093	50.242	5	0.247	5.920	0.5
11	2.134	51.210	5	0.243	5.84	2
12	2.093	50.242	5	0.247	5.920	2
13	2.093	50.242	5	0.247	5.920	0.5
14	2.094	50.259	4	0.433	10.40	2
15	1.888	45.316	4	0.423	10.16	2
16	1.929	46.284	5	1.254	30.12	4
17	2.100	50.406	5	0.0417	10.20	2
18	2.130	51.135	5	1.285	30.84	4
19	2.132	51.180	5	1.285	30.84	4
20	2.134	51.214	5	1.285	30.84	2
21	2.135	51.247	5	0.455	10.92	2
22	2.130	51.130	5	0.455	10.92	2
23	2.133	51.214	5	0.455	10.92	3
24	2.104	50.492	5	0.66	15.84	3
25	2.100	50.410	5	0.63	15.12	3
26	2.100	50.423	5	0.63	15.12	3
27	2.104	50.488	5	0.63	15.12	3
28	2.106	50.537	5	0.63	15.12	3
29	2.137	51.277	5	0.63	15.20	3
30	2.164	51.935	5	7.92	15.84	3

required limit of energy consumption, which will send a message to the consumer with the scheduled data of energy consumed at any time, which will let the consumer know the times during his day that the electricity consumption has exceeded, re-rationalizing consumption during these times before a residential bill comes that the consumer cannot afford. The flowchart of the P-EANN method is shown in Fig. 4.

In Table 3, the higher active power (kW) values for the electrical usage through twenty-four hours have a range of (2.096–2.164 kW) n the standard method, so the P-EANN method takes these values and makes management based on the ANN technology to give the suitable active power (kW) to become (0.247–7.92 kW) as shown in Fig. 5. Then, we can use these desired data to find the desired electrical usage.

The (E_c) (kWh) values in the standard method range from 50.323 to 51.935 (kWh), so here the electric output (E_c) values of the consumers are exceeding the useful learning rate. The variation and the (kWh) values range from 5.920 to 15.84 (kWh), and the P-EANN method predicts the new residential bills according to Table 3. It is clear from Table 3 that the residential bills based on PEANN cost an amount ranging between 0.5 to 3 $,

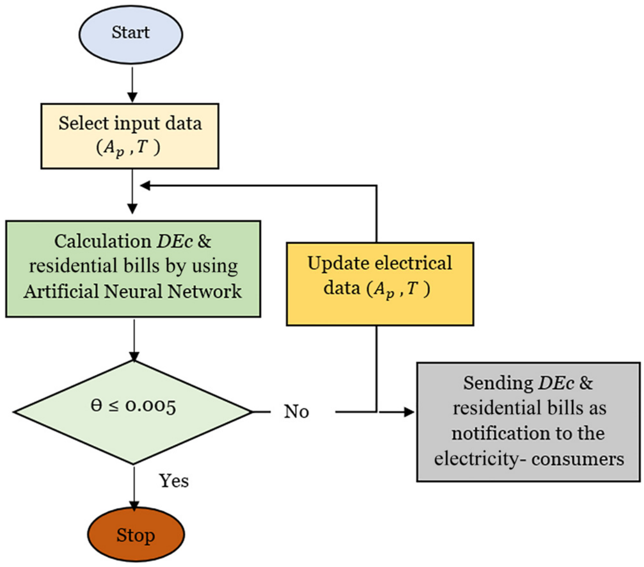

Fig. 4. The flowchart of the P-EANN method

whereas the bills cost an amount reaching up to 5 $ based on standard method. Through the results, we notice that there is a large gradient between the electricity values used

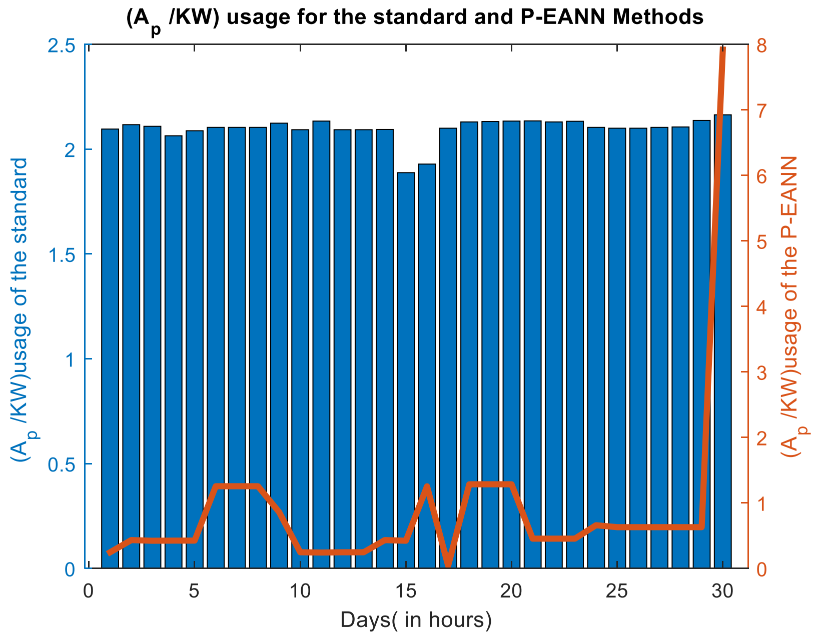

Fig. 5. (A_p) usage for the standard and P-EANN methods

in the usual method of measuring electric standard method and the amount of value that emerged from using the new forecasting method in P-EANN, as shown in Fig. 6, which shows the extent of the decrease in the amount of energy consumed within twenty-four hours a day and within one month.

Accordingly, it can be concluded that the amount of residential bills will be clear to us and specified in standard accurate numbers that are proportional to the amount of electricity consumed, which shows the extent of the decrease in the amount of residential bills, as shown in Fig. 7.

From the result of the KWh in Table 3, we took the root mean square error for each method to find which had more accuracy in finding the residential bills by using the formula in Eq. (16).

$$RMSE = \sqrt{\left(\frac{1}{30}\right)\sum_{1}^{30}(Ec - DEc)^2} \quad (16)$$

The electrical usage in the standard method is equal to 1.3140; this might be acceptable for finding the residential bills, but the P-EANN method is equal to 0.8450; this might

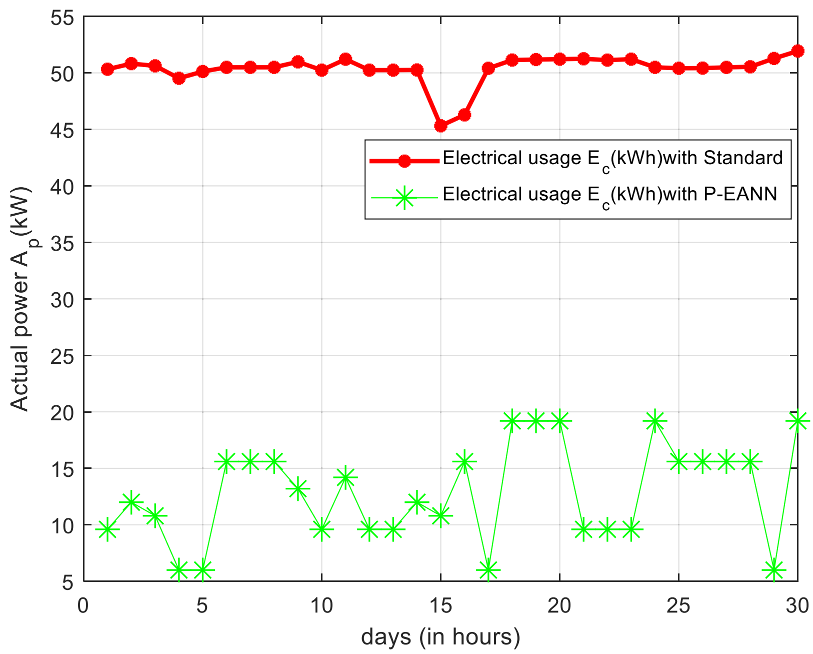

Fig. 6. Difference in electrical usage (KWh) in the standard method, a P-EANN method

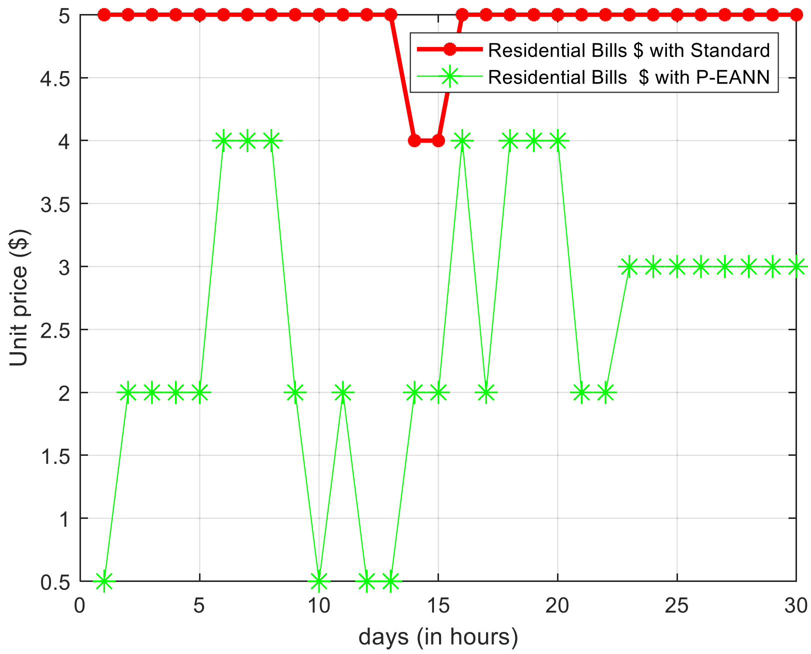

Fig. 7. Difference of residential bills ($) in the standard method vs. P-EANN method

be considered excellent accuracy in finding the residential bills, as shown in Table 4.

From the root mean square error for each method, we satisfied the P-EANN method, which has more accuracy and can be used to find the residential bills ($). The accuracy of the residential bills ($) from the red bar in the standard method is equal to 0.00%, but the accuracy of the residential bills ($) from the blue bar in the P-EANN method is equal to 35.69%, as shown in Fig. 8.

Table 4. The RMSE of the electrical usage between the standard and P-EANN method

Method	Standard	P-EANN
RMSE	1.3140	0.8450

The future extension of this study can be made either by introducing modern optimization techniques like Particle Swam Optimization (PSO), Social Spider Optimization (SSO), Whale Optimization Algorithm (WOA), Butterfly Optimization Algorithm (BOA), and Spotted Hyena Optimization (SHO) to optimally tuning the weights of neural network structure [31–43]. The real-time implementation of

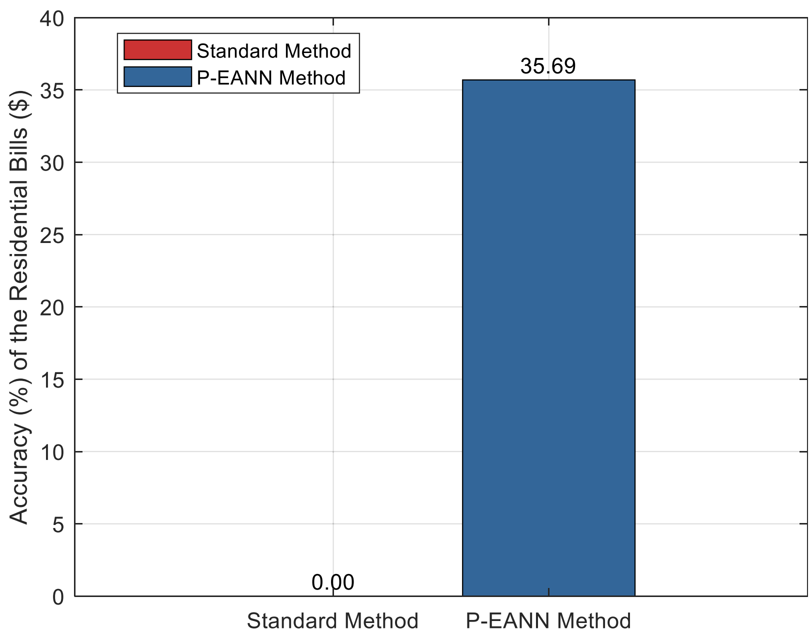

Fig. 8. Accuracy of residential bills ($) in the standard method vs. P-EANN method

xthe proposed neural network can be made using Raspberry-Pi microcontroller, FPGA, NI LabVIEW [44–48]. One can replace the conventional neural network by spiking neural network to improve the performance of neural network [49–51]. Another update of this study is to utilize the Deep learning neural network to replace the classical neural network [52–55].

5. CONCLUSION

In this study, two techniques are present to reduce overall residential bill costs without losing customer satisfaction: the standard method and an artificial neural network (P-EANN) method. The contribution that has been added to this proposed P-EANN method is to focus on predicting the values of electrical usage without being restricted by the number of devices and operating them at any time in the home for one month. This work also includes a notification that will be sent to people who exceed the specified limit of desired electrical usage, attaching with it the amount of electrical usage that they must implement, and an attachment to the list of new residential bills that they will receive if they commit to the specified schedule that includes the appropriate amounts of desired electrical usage that were sent to them. The P-EANN method is useful because it classifies the electrical loads in the house, and an ANN will be created for each house. The P-EANN method trains its functions until it reaches the appropriate ratio of the required electricity consumption, which is the least possible amount of electricity that a human can consume. The results of the MATLAB simulation of the P-EANN method showed that the appropriate training data for the users' residential bills was found. The values of the residential bills in the standard way have a maximum value of $5. Also, the maximum value of kWh in the standard method is 51.935 (kWh), and the P-EANN method processed the values of residential bills and updated its data so that the maximum predicted value is 3 dollars, and the maximum value of kWh is 15.84 (kWh). The P-EANN method enhances and reduces residential bills from 0.5 to 4.5 dollars per day. Thus, electricity consumption is rationalized, and energy sources are protected from depletion and loss, which finally means that they are more suitable for residential bills. The experimental work of the P-EANN method can be used to find the electrical usage and the residential bills for one year as future work.

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