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# Artificial Neural Network for Non-Intrusive Electrical Energy Monitoring System

**Khairell Khazin Kaman, Mahdi Faramarzi, Sallehuddin Ibrahim, Mohd Amri Md Yunus***
Innovative Engineering Research Alliance, Control and Mechatronic Engineering Departments,
Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 Johor Bahru, Johor, Malaysia
*Corresponding author, e-mail: amri@fke.utm.my

***Abstract***

*This paper discusses non-intrusive electrical energy monitoring (NIEM) system in an effort to minimize electrical energy wastages. To realize the system, an energy meter is used to measure the electrical consumption by electrical appliances. The obtained data were analyzed using a method called multilayer perceptron (MLP) technique of artificial neural network (ANN). The event detection was implemented to identify the type of loads and the power consumption of the load which were identified as fan and lamp. The switching ON and OFF output events of the loads were inputted to MLP in order to test the capability of MLP in classifying the type of loads. The data were divided to 70% for training, 15% for testing, and 15% for validation. The output of the MLP is either '1' for fan or '0' for lamp. In conclusion, MLP with five hidden neurons results obtained the lowest average training time with 2.699 seconds, a small number of epochs with 62 iterations, a min square error of 7.3872×10-5, and a high regression coefficient of 0.99050.*

***Keywords****: non-intrusive, electrical energy monitoring, multilayer perceptron, artificial neural network, Fluke 435 energy meter*



## 1. Introduction

Non-intrusive electrical energy monitoring (NIEM) is the process of detecting the changes in the voltage, current and collecting data about a load inside a building and without implementing a sub-meter infrastructure with a single set of sensor [1]. This configuration is in contrast to an intrusive method scheme which requires sensors on all of the devices. These sensors then communicate back to a central aggregation hub, which can be a part of the residential smart meter. Instead of having multiple sensors spread out on the appliance of interest, NIEM used only a single sensor located at the building service entrance [2]. The trade-off is that NIEM requires much more signal processing and analysis than a distributed metering scheme would need, especially if the system is autonomously learning about the loads inside the home without human intervention.

There are mainly three categories of nonintrusive disaggregation algorithm and methods which are the wavelet transform (WT), support vector machine (SVM) and artificial neural network (ANN). Chan et al, explained that the fuzzy numbers are used for the harmonic signature recognition for WT [3]. They have made use of new development in wavelet so that each type of current waveform polluted with power harmonics can be well presented by a normalized energy vector consisting of five elements [4].

A support vector machine (SVM) generally practiced using a randomly selected training set which is classified in advance [5]. SVM is a classifier that gives a set of training example with each marked as belongings to one of two categories. The third method is the neural network that is applied in this project as an analysis method. The use of neural network classifies to evaluate back propagation (BP) and learning vector quantization (LVQ) for feature selection of load identification in NIEM.

The back propagation of neural network was selected due to the general nature of the BP training method means that a BP net (a multilayer, feedforward net trained by BP) can be used to solve problems in many areas with a simpler method and stages. Training a network by BP involved three stages which are the feedforward of the input training patterns, the BP of the associated error and the adjustment of the weights [6-8]. ANN is a reliable forecasting method in

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many applications, nevertheless load identification is a difficult task. The main reason is because the electrical consumption measured from the loads is complex and seasonal variation: the power consumption at any particular hour is dependent on the power consumption on the previous hour, the same hour on the previous day, and on the same hour on the same day of the previous weeks. Moreover, uncertain bad weather conditions such as thunderstorms with lightning can be a source of false identification and error.

## 2. Research Method

This section explains the appropriate method used to analyze the data obtained from the Fluke 435 power quality analyzer energy meter. The connection of smart meter to the load is shown in Figure 1. The structure of the method consists of three signal processing parts. It describes that the power measurement using NIEM technique where the sensor is placed at the main supply of the distribution board. Then the event detection is implemented before the data is classified using MLP technique of ANN.

In the first part, the harmonic load bank is identified as the load supplier. It provided three different type of lamps with a specified power rating for each type. The experimental setup used the type of lamp without a ballast and power rating of 21 W. The power rating for fan is specified as 50 W and connected at the output socket from the load bank for measurement purpose. The power measurement was conducted using the Fluke 435 power quality analyzer energy meter under a set of controlled load turn on and turn off sequence.

The MATLAB software is used to implement the algorithm of events detection in the second part. The data must be sufficient in order to train the ANN so that it will comply with the data division of 70 % for training, 15 % for testing and another 15 % for validation. The last step in methodology is the analysis part where the ANN is developed to train the data using the MLP technique. The outputs from the MLP classify the types of load into a range of ‘1’ for fan and ‘0’ for lamp. The output is observed in terms of the Mean Square Error (MSE) and a regression plot to specify the good classification output.

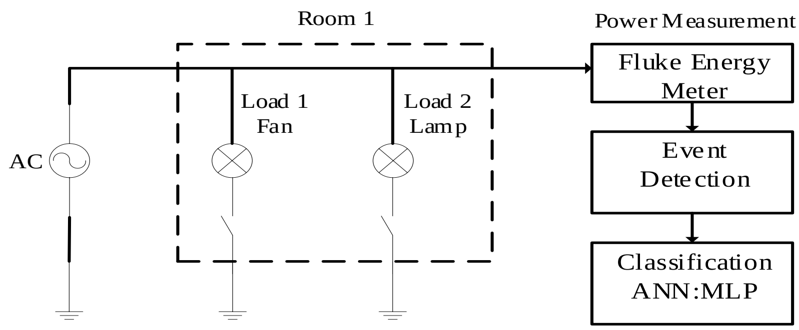



Figure 1. Smart meter approach using ANN

### 2.1. Power Measurement

The Fluke Power Quality Analyzer as shown in Figure 2a was used as the energy meter to measure the power consumption by the loads which consist of fans and lamps. These two type loads are chosen because they are common appliances used in a house. The power ratings for the loads are specified as 50 Watts (W) for the fan and 21 W for the lamp. Fluke energy meter offers an extensive set of measurements to check power distribution systems and provided data logging to record and collect data [9]. Software provided by the Fluke Corporation called Power Log is used to download the measured data with the power consumption pattern and appropriate configuration of measurements as shown in Figure 2b.

(a)

(b)

Figure 2. (a) Fluke energy meter (b) Configuration of power measurement

## 2.2. Switching Event Detection Algorithm

The event detection algorithm is used to find the starting operational point of an appliance before the classification of an appliance can be carried out. There are three main requirements of an event detection algorithm which are timeless, a high true detection rate, and a low false alarm rate. The events are changes in the signal-curve where it gives different kinds of events, continuous, and abrupt. For the detection of events in the signal power, a method called the step detection method is used. Generally, there is a difference between two kinds of abrupt events such as 'Switching ON Events (SwON)' and 'Switching OFF Events (SwOFF)' [10, 11].

Figure 3 shows the SwON and SwOFF events called an operational sequence for the fan and lamp where the thresholds are set to specify the system for SwON and SwOFF to occur [11]. The threshold for SwON is set to 30W for lamp, 50W for fan while the threshold for SwOFF is set to 20W for lamp, and 35W for fan. The equations to calculate the delta power $\Delta P$ are shown in equations (1) to (6).

The Hart approach used the delta values to find the switching events and to classify the appliances in the classification stage [12]. The delta values are:

$$Delta\ Power, \Delta P = P(t) - P(t - \Delta T) \quad (1)$$

$$Delta\ Time, \Delta T = 2\ s \quad (2)$$

The current power value, $P(t)$ subtracts the power value $P(t - \Delta T)$. If the result is greater as a predefined threshold, a switching on event is detected based on equations (3) and (4). In this approach a power threshold of 70W is used. The second parameter is the time $\Delta T$ between the two power values. This time is necessary to wait until the appliance behaviour is in a steady state. For the time delay Hart set $\Delta T$ to 2s [12].

$$SwON\ Event = \Delta P \geq Threshold \quad (3)$$

$$SwON\ Event = P(t) - P(t - \Delta T) \geq Threshold \quad (4)$$

The second kind of abrupt events which is the switching off events can be calculated based on equations (5) and (6) where the threshold must be negative. The classifier can classify the appliances after the switching events are obtained.

$$SwOFF\ Event = \Delta P \leq Threshold \quad (5)$$

$$SwOFF\ Event = P(t) - P(t - \Delta T) \leq Threshold \quad (6)$$

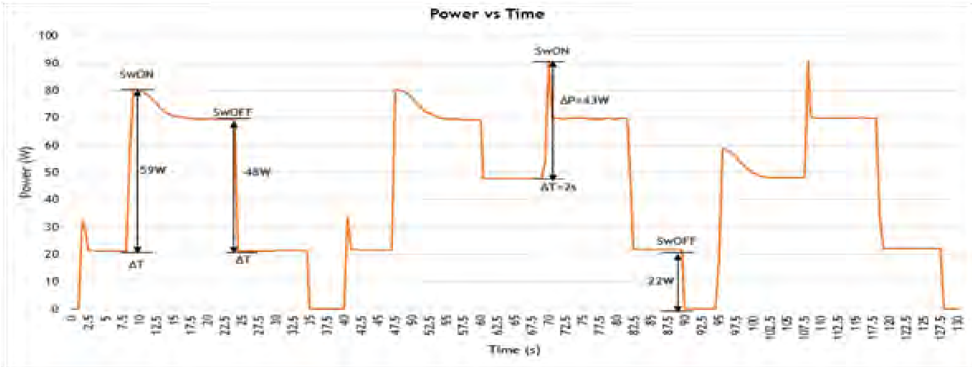


Figure 3. SwON and SwOFF events for the fan and lamp

### 2.3. Architecture of ANN

A neural network is characterized by its pattern of connection between the neurons, methods of weight adjusting (learning process) and its activation function. It uses either nonlinear or linear functions to model a neuron. The artificial neuron deals with the selection of hidden layer and hidden neurons, depending on the number of input and training set to obtain the best output results as shown in Figure 4.

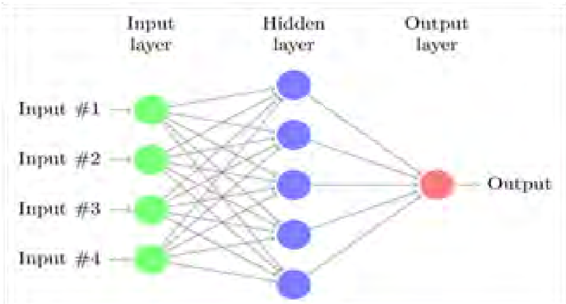


Figure 4. Neuron Networks in ANN

### 2.4. Experimental Setup

The experimental setup for this work is illustrated in Figure 5. The setup involved the use of the Fluke energy meter, a personal computer for transferring data, a harmonic load bank that provided the lamp, and the fan. The harmonic load bank provided three different types of lamps with a specified power rating for each type. The experimental setup used the type of lamp without ballast and with a power rating of 21 W. The power rating for fan is specified as 50 W and connected at the output socket from the load bank for measurement purpose.

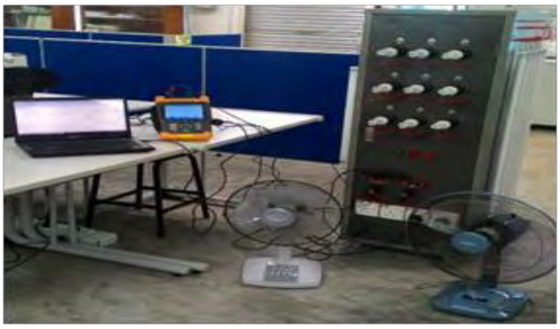


Figure 5. Experimental setup for data collection

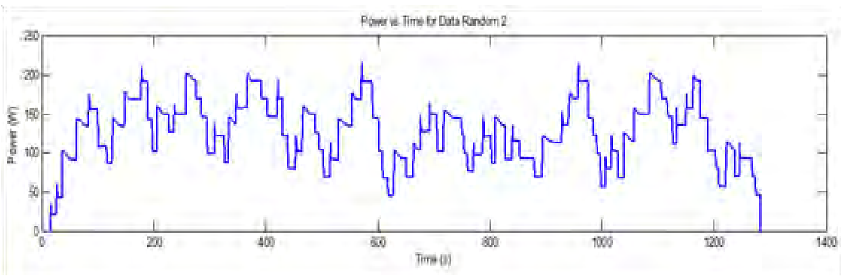
Table 1 simplified the operational sequence of load measurement, involving three sets of lamps and fans in the load bank. There were also sets of randomly operational sequences where the fan and lamp were switched ON and OFF randomly.

Table 1. Operational sequence for trials

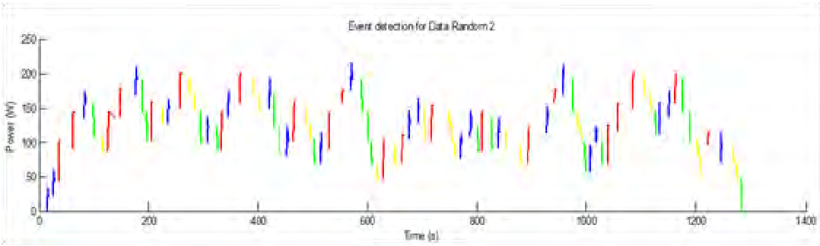
| Trials | SET 1 | SET 2 | SET 3 |
|---|---|---|---|
| 1 | LAMP AND FAN ON | LAMP AND FAN OFF | LAMP AND FAN OFF |
| 2 | LAMP AND FAN OFF | LAMP AND FAN ON | LAMP AND FAN OFF |
| 3 | LAMP AND FAN ON | LAMP AND FAN ON | LAMP AND FAN OFF |
| 4 | LAMP AND FAN OFF | LAMP AND FAN OFF | LAMP AND FAN ON |
| 5 | LAMP AND FAN ON | LAMP AND FAN OFF | LAMP AND FAN ON |
| 6 | LAMP AND FAN OFF | LAMP AND FAN ON | LAMP AND FAN ON |
| 7 | LAMP AND FAN ON | LAMP AND FAN ON | LAMP AND FAN ON |

## 3. Results and Analysis

Figure 6(a) depicts the output power versus time and Figure 6(b) shows the respective event detections. The switching ON event (SwON) consists of event for fan (red line) and lamp (blue line), while the switching OFF event (SwOFF) include the event for fan (green line) and lamp (yellow line). The event detection algorithm counts the events as the data is be fed into the MLP network for the classification. The five-point technique is used after the delta power, $\Delta P$ is calculated, which means there are five successive equal interval data points along the switching event as shown by the black dots in Figure 7.




(a)




(b)

Figure 6. (a) Output power versus time (b) Event detection for random sequence

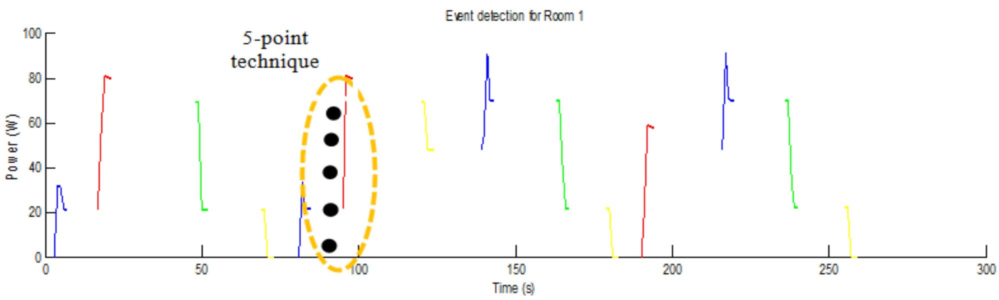


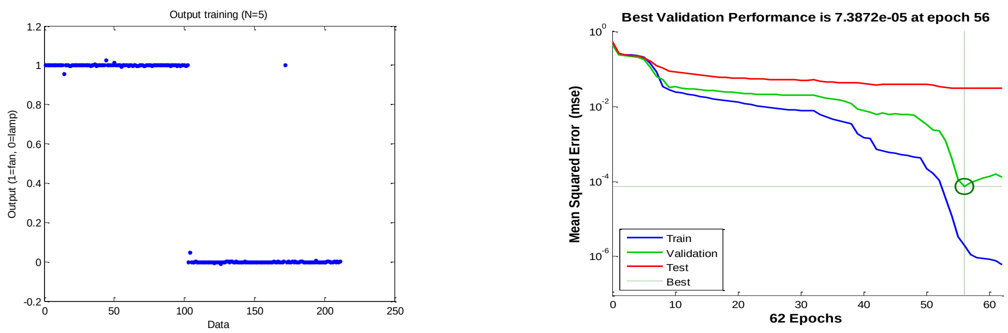

Figure 7. The five-point technique applied in event detection algorithm

### 3.1. Output Classification of the Loads

There are nine sets of data that produced 286 switching ON and switching OFF events. The events were conducted in a certain sequence and in a random manner to test the capability of the MLP network to classify the loads. The events are divided into three parts which are 70% (200 events) is used for training, 15% (43 events) for testing and another 15% (43 events) for validation

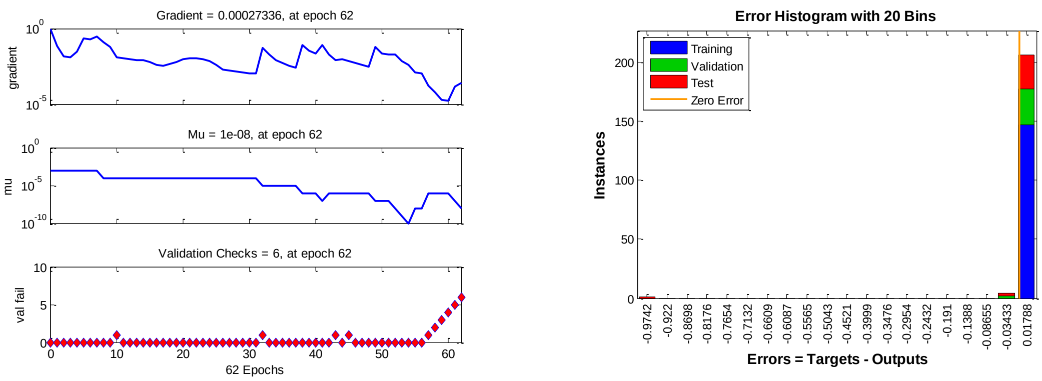
Figure 8 (a) describes the output training for five neurons in the hidden layer (N=5), with corresponding performance analysis figures. The sigmoid functions are applied to the neurons in the hidden layer and the linear functions are used for the single neuron in the output layer. The output training in Figure 8(b) displays a good classification of loads by the MLP network where all the data lies on the specified target with $\pm 0.2$ tolerance ('1' for fan and '0' for lamp). The performance indicates that there is a low MSE which equals to $7.3872\times10^{-5}$ at epoch 56 and the training continued for six more iterations before the training stopped. The test MSE curve is gradually decreasing as the validation MSE is decreasing, since the test curve is not increased significantly before the validation curve increased, so over fitting does not occur during the training.

Figure 9(a) shows that the gradient reach the bottom of the local minimum with a value of 0.00027336 and the validation fail stopped at epoch 62 after six consecutive fails. The validation vectors were used to stop the training process if the network performance failed to improve or the performance remained the same for six iterations in a row. Furthermore, the error histogram shows a good classification with only a few outliers' data at -0.9742 (testing) and -0.03433 (validation and testing), while most of the data lies within the 'zero error' line at $0.01788$ as shown in Figure 9(b). The regression coefficients the training, testing and validation *R* values are 1, 0.93759, and 0.99986, respectively. The overall regression is 0.9905, which indicates that the output is almost an exact linear relationship between the output and the target.




(a) (b)

Figure 8. (a) Output training for hidden neuron, N=5 (b) performance of train, validation, and test processes




(a) (b)

Figure 9. (a) Training state performance (b) Error of train, validation, and test processes

## 4. Conclusion

The nonintrusive electrical energy monitoring (NIEM) is used since the method is effective for collecting end-use load data of appliances. It is simpler compared to IEM method, but NIEM requires a comprehensive algorithm to identify the type of loads and to classify correctly.

Hence, a method called ‘Smart Meter Approach Using ANN’ is applied which include the power measurement using a Fluke energy meter and the event detection to identify the switching ON and OFF of the loads. Finally the approach implement the MLP network of ANN to classify the type of loads within the range of ‘1’ for fan and ‘0’ for lamp. By analysis and comparison, it can be concluded that the configuration with one hidden layer and five neurons are the best configuration obtained in the network training.

The best results obtained has a lower average training time of 2.699 seconds, a small number of epochs of 62 iterations, the lowest MSE of 7.3872×10-5, and a high regression coefficient value of 0.99050. These results show that the proper configuration and network training determines the accuracy of the classification of the loads.

A few future recommendations are proposed. Firstly, it is proposed that, a low cost energy meter Integrated Circuit (IC) ADE7753 to be constructed with features of a single phase multifunction metering IC and di/dt sensor interface. The low cost energy meter can be built to incorporate an Arduino microcontroller, where it can be directly connected to the MATLAB software for data transfer and further analysis.

Secondly, a wireless monitoring system using Ethernet or Xbee module to monitor the power consumption on-line and directly classify the load using the MLP network is proposed. This method can collect data within a long range in a control room with a proper interface using MATLAB or LabView. Last but not the least, the analysis method can be improved by applying another analysis method, for an instance, the Hidden Markov Model can be used to compare the architecture, algorithm, and the performance with the MLP network.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