Development of Arduino Microcontroller Based Non-Intrusive Appliances Monitoring System Using Artificial Neural Network

Article *in* Journal of Computational and Theoretical Nanoscience · June 2018

DOI: 10.1166/asl.2018.11631

Mohd Wazir Mustafa
Universiti Teknologi Malaysia

Hussain Shareef
United Arab Emirates University

Development of Arduino Microcontroller Based Non-Intrusive Appliances Monitoring System using Artificial Neural Network

I. Abubakar[1], S. N. Khalid[1*], M. W. Mustafa[1], M. Mustapha[1] and Hussain Shareef[2]
[1]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Johor Bahru, 81310, Johor, Malaysia;
[2]Collage of Engineering, United Arab Emirates University, Al Ain, UAE;
aisiyaku2@live.utm.my, nizam@fke.utm.my, wazir@fke.utm.my, mamunu33@gmail.com, shareef@uaeu.ac.ae

Abstract

Background/Objective: Non-Intrusive Load Monitoring (NILM) is a process of identifying the connected loads in a premises from the measurements obtained at the service entry. That is, through NILM one can tell the operating conditions (ON or OFF) of the house appliances from the aggregated measurements taken at the service drop. The method is more advanced than the traditional method which require measuring sensors for every load of interest. In an effort to explore the applicability of NILM in home appliances' recognition, this paper presented the development of a home NILM using arduino microcontroller. **Methods/Statistical Analysis:** Aggregated real power (P), rms current (Irms) and power factor (pf) of the connected appliances are used as an offline data to train a feed forward ANN whose output is the pattern of the connected loads. Four different home appliances are experimented in generating the training data and the ANN model is implemented in the arduino program to identify the loads. **Findings:** Experimental analysis on the monitoring system shows that it can accurately recognize the load patterns when the supply voltage is within the range of 240V and the pattern may not be recognized when the input voltage deviated from 240V. **Applications/Improvements:** The developed system can be applied into home appliances management and control for efficient energy utilization, the operation of which can be assessed without entering into the consumer privacy.

Keywords: Voltage sensor, Load monitoring, Power Measurement, Energy management, Feed Forward Neural Network, Arduino Microcontroller.

1. Introduction

Over the last two decades the Non-Intrusive Load Monitoring (NILM) is gaining popularity and there had been so many research works in the area. Before the advent of NILM, the traditional load monitoring used to be intrusive in nature, which means a sensor or group of sensors will be assigned to every load of interest in order to monitor the power consumption or the operating conditions of the individual loads in the system. This type of monitoring is referred to as Intrusive Load Monitoring (ILM). The NILM on the other hand utilizes only one set of sensing or measuring devices at the service entry to capture the measurements of the aggregated loads. Through algorithm, these measurements are converted into signatures or features for disaggregating/recognizing the connected loads[1-4]. The NILM is simple and cost effective for its single point sensing, whereas ILM is costly due to its multiple sensing points and complex in installation[5].

The issue of optimizing energy usage through load management is a very vital issue in the energy world and the knowledge of the energy consumption of the individual appliances is the fundamental action in energy management. Studies have shown that if the actual energy consumption of each load is made available to the consumers, that will encourage them to conserve the energy which will help the utility companies and government to device energy saving policies[6]. The application of NILM in appliance energy management is a very good choice because of its simplicity and non-

Author for correspondence

intrusiveness, which render its system accessible without disturbing the consumer privacy [7]. In this research focus is made on the real time application of NILM to monitor operating conditions of the house appliances non-intrusively. Most of the previous works in NILM concentrated in developing the disaggregation procedures and signature extraction [8,9]. There is need to come out with a standalone NILM system that can be applied to recognize the operating condition of the utility for the purpose of management, especially in residential settings.

In this paper a house monitoring system is developed in the form of NILM using arduino microcontroller and ANN. The system used experimental data from four typical house loads with the aggregated real power, current and power factor of the connected loads as the input signature and the load pattern as the output. This data generated through measurement using arduino microcontroller, current and voltage sensors, is used to train a feed forward ANN for recognizing the patterns of the loads. The model of the trained ANN is then implemented in the arduino program for the load recognition. All the times the system will measure the aggregated quantities and use them to recognize the connected loads. The research work explores more opportunity of using NILM to monitor the operating conditions of the house appliances, which is an addition to the efforts of the researchers in finding more accurate disaggregation and signature extraction methods.

The remaining parts of the paper is organized as follows: Section 2 presents the Literature Review in the related area, section 3 provides the Methodology with Results and Analysis in section 4 and finally section 5 provides the Conclusion.

2. Literature Review

2.1 An Overview of Applied NILM Systems

The idea of NILM was discovered by G. W. Hart in 1980s in Massachusetts Institute of Technology. He was analyzing an aggregated electrical measurement when he discovered that the aggregated data can be used to know the energy consumption of the individual loads[1]. His method used the steady state variation of the real power and reactive power to detect the operating conditions of the loads using ΔP - ΔQ plane. Of cause Hart's work was based on the assumption that each load in the system consumes a unique value of real and reactive power. Over the last decades the work was followed by the contributions of hundreds of researchers in the area, which lead to the exploration of different appliance signatures and different disaggregation algorithms[10-14].

M. S. Tsai and Y. H. Lin[10] proposed a Non-Intrusive Appliance Load Monitoring system which comprises of feature extraction and feature optimization to identify the operating status of individual appliances. The system used Genetic Algorithm (GA) with fisher criterion to extract the feature of appliances, and it uses k-Nearest Neighbor Rule (k-NNR), Back Propagation ANN and Learning Vector Quantization (LVQ) to perform the identification. The identification result shows that the system can identify the operation of both single loads and multiple loads and that the k-NNR outperform the other methods. However in real situation there are difficulties associated with the capturing of the turn-on and turn-off transient measurements. Y. Kim et al[11] developed an electrical event identification technique for home appliance monitoring using signatures. The system uses NILM techniques with k-NNR as the identifier. The system achieved over 90% performance when identifying three loads, though the system requires further research to extend the range of identifiable events. H. H. Chang et al[14] combined the steady state Real Power (P), Reactive Power (Q) and the total Turn-on Transient energy (UT) to disaggregate different appliances with the same real and reactive power. The recognition accuracy of the system is far better with the combined signatures than when only the steady state signatures are used. 100% recognition is obtained when tested on three loads even though capturing the turn-on transient energy in real situation may also come with difficulty.

Some of the researchers applied the NILM in coming out with monitoring systems that can be applied in a utility[15-18]. A. Shrestha et al[15] uses network of non-intrusive load monitors in the development of dynamic load shedding for shipboard power. The system utilizes the transient signatures of the loads and disaggregate the loads for the dynamic load shedding scheme and the results obtained demonstrated the effectiveness of the method. Ninad K. et al[16] developed a non-intrusive load monitoring using zigbee protocol. The major purpose of the system is to maintain the power consumption below the threshold value by reducing the loads according to priority when the system is overloaded. M. N. V. Perez[18] developed a non-intrusive loads monitoring system for identifying kitchen activities. The system can accurately identifies the kitchen activities with some appliances though the larger the number of appliances the greater the difficulty of identification. Advances in wireless communication also provides opportunities for researchers to developed efficient and reliable load monitoring systems[19].

2.2 The Feed Forward ANN

The feed forward ANN is one the tools used in pattern recognition method of disaggregating the loads in NILM[2]. It is an ANN that do not form cycles in the connections between its layers, therefore the information only flows in the forward directions, unlike what is applicable in Recurrent Neural Networks. Moreover there is no connection within the perceptron of the same layer in the feed forward ANN. Figure 1 shows the feed forward ANN with one hidden layer, four inputs and two outputs.

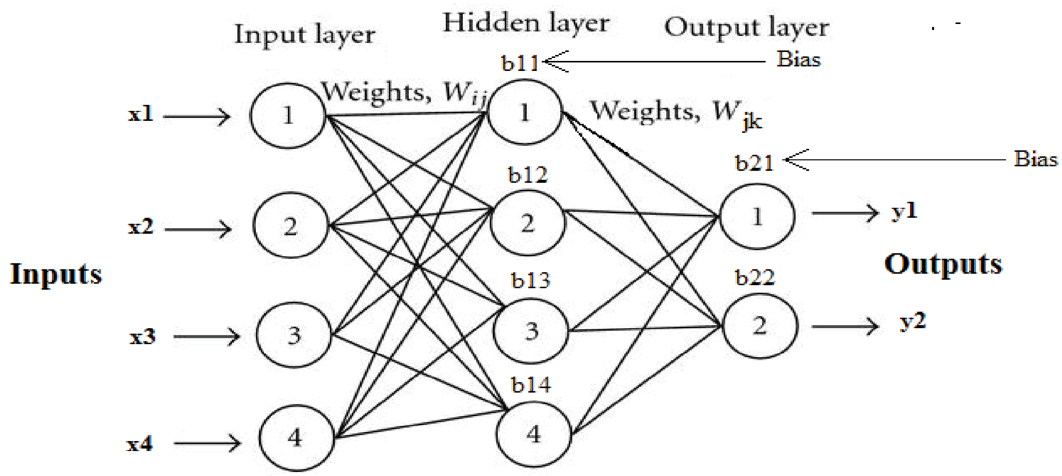


Figure 1. Feed Forward ANN with one hidden Layer

The ANN is normally trained to perform arbitrary mapping of one vector space (the inputs) into another vector space (the outputs). The training or learning of the neural network just means adjusting the weights, biases and activation functions for the inputs to be mapped into the outputs with highest possible accuracy[20]. The feed forward network can easily be implemented in any programming because of its simplicity and straight forwardness.

2.3 Arduino Microcontroller

The Arduino microcontroller is a single board processor that can be applied in a number of intelligent projects that involved control, computation, logical and sensing applications. Moreover, the arduino board is in expensive with extendable hardware and software that works across so many platforms, which makes it easy to be used in designing projects and prototypes. The programming language of the arduino is a simplified version of C++ language and the board comes in many forms including Arduino MEGA, Arduino nano and Arduino UNO. Figure 2 shows the pictures of some arduino boards. The microcontroller gets the voltage and current values from the sensors and manipulate them to get the other electrical quantities through computations.

Figure 2. Arduino Boards

2.4 Load Monitoring Tools

Energy management of the electrical appliances can only be achieved via proper monitoring of the load consumption. Before the advancement of ILM and NILM, the energy monitoring relies on only the utility meter readings, which was just the total energy consumption of the premises. Advances in electronics and telecommunication lead to the advancements of energy monitoring devices that have been applied in so many energy monitoring researches[6]. The energy monitoring devices can be categorized into Measuring Devices, Communication Devices, Optimization Devices, Recognition Devices, Control Devices and Display Devices. These devices include; current sensor, voltage sensor, smart meter, PCs, WIFI, zigbee, microcontroller, relays, smartphones and LED display.

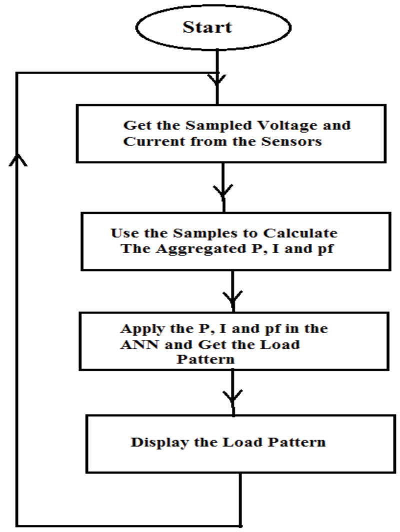


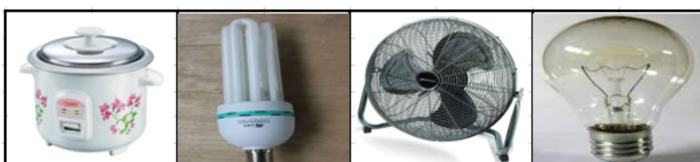
Figure 3. The Flowchart of the System

3. Methodology

The work in this research involves the measurement of the aggregated real power, current and power factor of the connected loads using arduino micro controller, voltage and current sensors. The ZMPT101B voltage sensor module calibrated in[21] and ACS716 current sensor (which is factory calibrated) are used. The arduino programming code include the model of the feed forward ANN that identifies the connected loads when it received the aggregated measurements above. Initially a data of the aggregated quantities against the load pattern is generated using the arduino set and four typical house appliances. These appliances are 120W light bulb, an Energy saving light, a Table fan (only high speed used) and a Rice cooker (in the cooking mode). Figure 3 shows the flowchart of the system.

3.2 Data Collection

Instantaneous calculation is used in calculating the total power consumption of the system from the samples of voltage and current collected from the sensors[21]. This instantaneous calculation makes the total power and other quantities to have a little variations over the cycles of the operations of the microcontroller. For each load combination 8 different records of the aggregated data are taken. Hence a data of 128x7 is generated and in each load combination the data is arranged in ascending order of the power consumption. Six data is selected to be the training data in each load combination and the remaining 2 data is used for simulation, this make a total of 96x7 data for training and 32x7 for simulation. Figure 4 shows the training data for one of the loads combinations of the system.



				POWER, P(W)	CURRENT, I(A)	POWER FACTOR,pf
1	0	1	0	559	2.75	0.87
				561	2.78	0.87
				562	2.72	0.89
				562	2.75	0.88
				564	2.70	0.90
				565	2.78	0.88

Figure 4. Sample of the Data for a Combination of Loads.

3.3 The Feed Forward ANN Training

The feed forward ANN is trained using the data generated. The load pattern is the output of the network whereas the Power, Current and Power factor are the inputs to the network. Hence there are three input neurons and four output neurons. Only one hidden layer is used for this work to enable easier implementation of the network model in the arduino program. Out of the 128 set of data 96 data (6 from each load combination) is used in training the network the remaining 32 is used in simulating the network to observe how it fit the input to the output. In each training and retraining, which involved changing the number of hidden neurons and activation functions, the performance of the network is observed. The network should have least possible number of neurons in the hidden layer to avoid complexity in the arduino programming[20].

3.4 The Arduino Programming Code

The program will first capture the aggregated measurements of the Power, Current, and Power factor using the samples from the voltage and current sensors. These aggregated values are then passed into the network model to determine the connected loads which will be displayed on the LCD. Figure 5 shows some part of the ANN model in the arduino program.

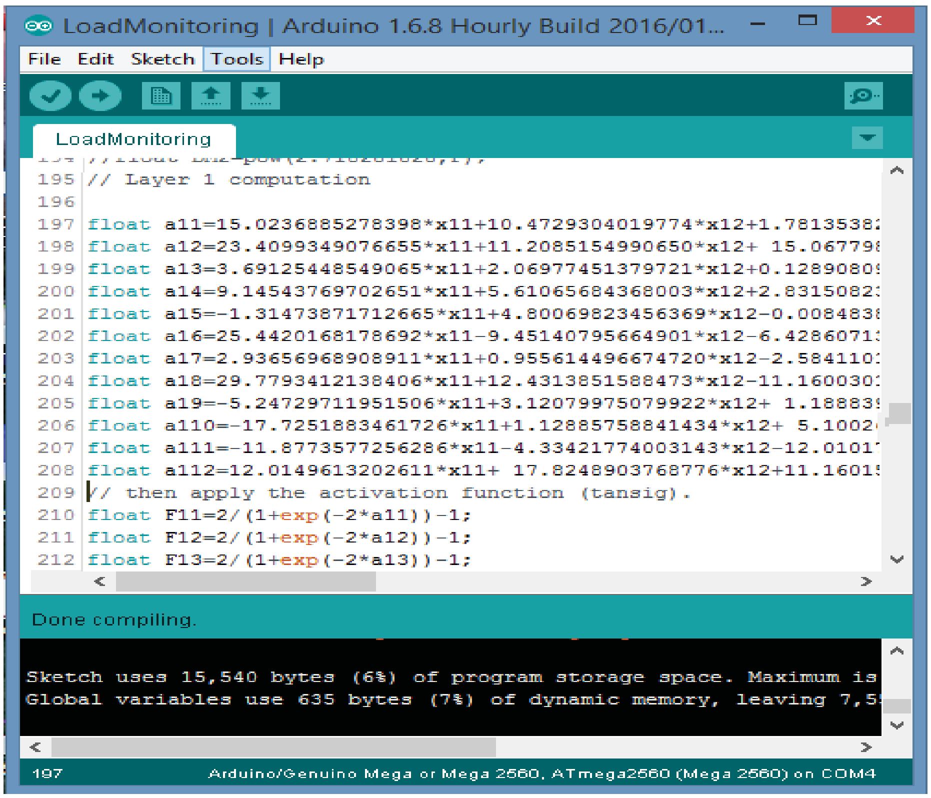


Figure 5. The Arduino Program

4. Results and Analysis

The results in the work consists of the ANN training results and the system performance results. The general analysis of the system then followed.

4.1 The Feed Forward Network Training Results

After each training of the network the regression analysis is observed and training is repeated until the best performance is observed with 12 neurons in the hidden layer, tansig activation function in both the hidden layer and the output layer, and 48 epoches. The training regression is 0.98322 and overall regression is 0.98068. Figure 6 gives the diagram of the network and figure 7 are the training performance. The network is also simulated with the 32 simulating data again and the plots of the real outputs against the simulated outputs is given in Figure 8

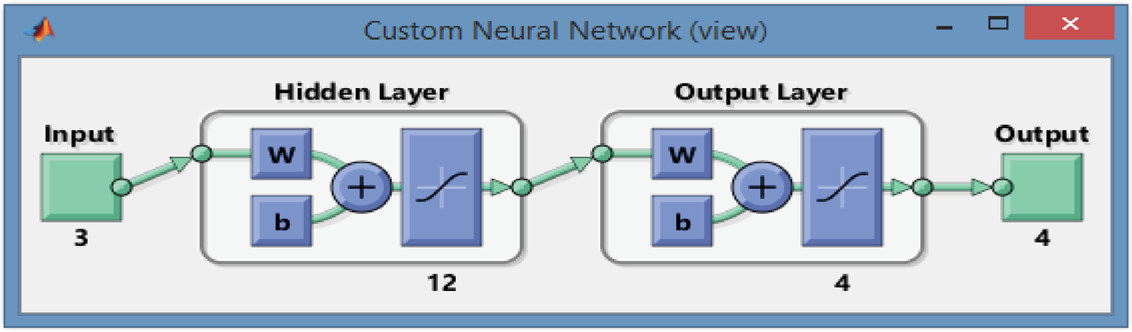


Figure 6. The Trained Network

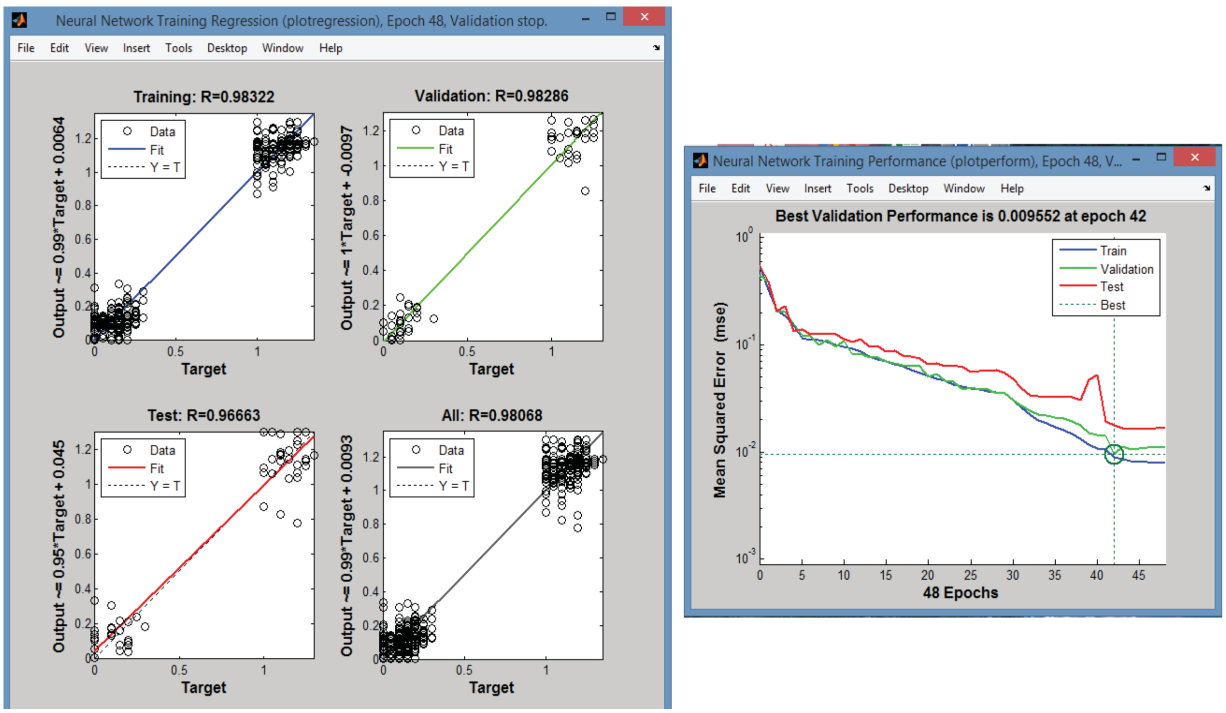


Figure 7. The Network Training Performance

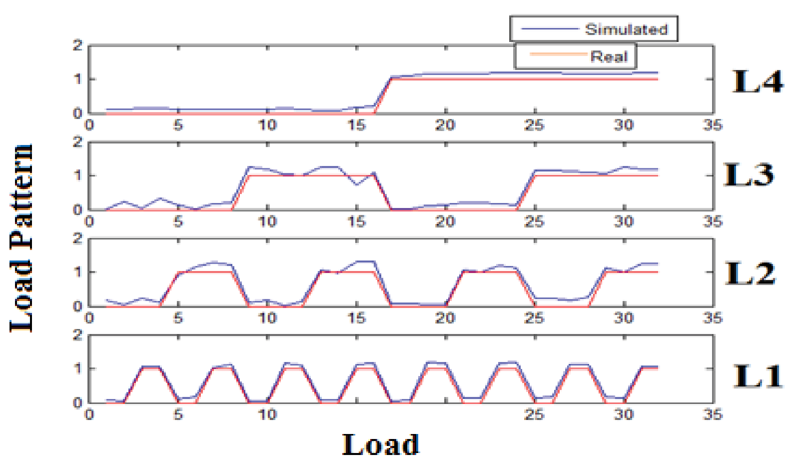


Figure 8. The Simulation Result

4.2 System Performance

The output of the network as shown in Figure 8 is a decimal number unlike the real output which is in form of binary (0 and 1). But never the less when the simulated output is approximated to the nearest whole number, it fits exactly on the real output. This approximation is performed in the arduino program. All the load combinations are tested and the corresponding load pattern is displayed on the LCD as shown in Figure 9.

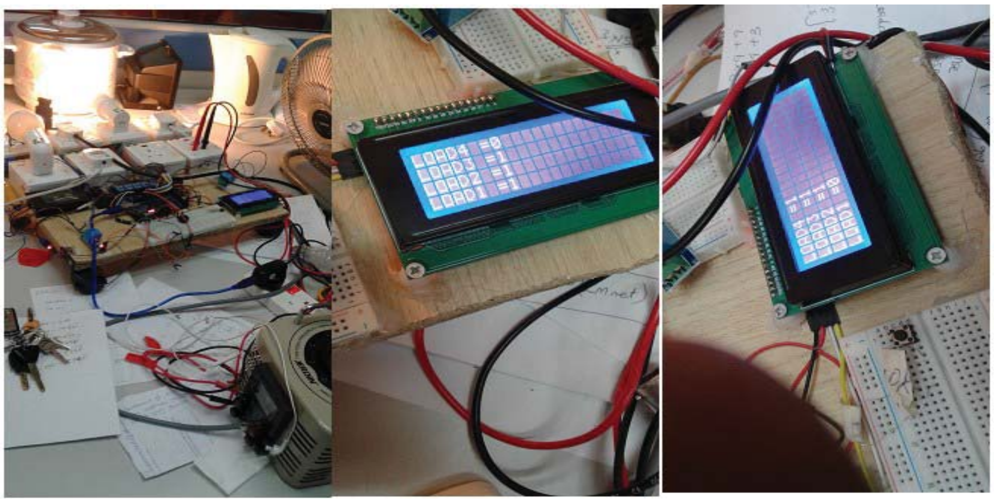


Figure 9. The System

4.3 General Analysis

As mentioned earlier, due to the instantaneous power calculation, which uses the samples of the voltage and current to calculate the power, the measurements are always fluctuating. Even though the system identifies the loads with this fluctuations, but sometimes there is voltage drop in the laboratory from the normal 240V to around 232V when so many loads are connected. When the voltage drop to that level the load recognition is not achieved with some load combinations. Also there is no diversity in the power factor from one combination to the other among the majority of the load combinations. Also in one or two cases there are load combination with closer power consumption.

5. Conclusion

This work presented the development of a non-intrusive home appliances monitoring using microcontroller and feed forward ANN model as the identifier. The system is capable of identifying all the combination of the four loads experimented and the little fluctuation in the measurement does not affect the result. The drop in the supply that hinders the pattern recognition can be taken care of if there is a stabilized voltage supply or the experiment can be extended to include the voltage in the load signatures. Also if the loads to be monitored have much differences in the power factor that will also ease the identification which may lead to the reduction of the neurons in the network. Future works in this research will include using the system to facilitate energy management and control of the home appliances.

6. Acknowledgement

The authors would like to acknowledge the Universiti Teknologi Malaysia and the Ministry of Education (MOE) Malaysia for supporting this work.

7. References

1. Hart GW. Nonintrusive appliance load monitoring. Proceedings of the IEEE 1992;80(12):1870-91.
2. Zoha A, Gluhak A, Imran MA, Rajasegarar S. Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey. Sensors 2012;12(12):16838-66.
3. Guo Z, Wang ZJ, Kashani A. Home appliance load modeling from aggregated smart meter data. IEEE Transactions on Power Systems 2015;30(1):254-62.
4. Abubakar I, Khalid S, Mustafa M, Shareef H, Mustapha M. Application of load monitoring in appliances' energy management–A review. Renewable and Sustainable Energy Reviews 2017;67:235-45.

5. Chang H-H. Load identification of non-intrusive load-monitoring system in smart home. WSEAS Transactions on Systems 2010;9(5):498-510.
6. Yung Fei W, Ahmet Sekercioglu Y, Drummond T, Voon Siong W. Recent approaches to non-intrusive load monitoring techniques in residential settings. In: Computational Intelligence Applications In Smart Grid (CIASG), 2013 IEEE Symposium on, 16-19 April 2013; 2013. p. 73-9.
7. Christensen D, Earle L, Sparn B. NILM Applications for the Energy-Efficient Home. Contract 2012;303:275-3000.
8. Kim H, Marwah M, Arlitt MF, Lyon G, Han J. Unsupervised Disaggregation of Low Frequency Power Measurements. In: SDM: SIAM; 2011. p. 747-58.
9. Srinivasan D, Ng W, Liew A. Neural-network-based signature recognition for harmonic source identification. Power Delivery, IEEE Transactions on 2006;21(1):398-405.
10. Tsai M, Lin Y. Development of a non-intrusive monitoring technique for appliance'identification in electricity energy management. In: Advanced Power System Automation and Protection (APAP), 2011 International Conference on: IEEE; 2011. p. 108-13.
11. Youngwook K, Seongbae K, Rakkyung K, Sung-Kwan J. Electrical event identification technique for monitoring home appliance load using load signatures. In: Consumer Electronics (ICCE), 2014 IEEE International Conference on, 10-13 Jan. 2014; 2014. p. 296-7.
12. Amenta V, Gagliano S, Tina GM, Di Modica G, Tomarchio O. Web interactive non intrusive load disaggregation system for energy consumption awareness. In: AEIT Annual Conference, 2013, 3-5 Oct. 2013; 2013. p. 1-6.
13. Duarte C, Delmar P, Goossen KW, Barner K, Gomez-Luna E. Non-intrusive load monitoring based on switching voltage transients and wavelet transforms. In: Future of Instrumentation International Workshop (FIIW), 2012, 8-9 Oct. 2012; 2012. p. 1-4.
14. Chang H-H, Lin C-L, Lee J-K. Load identification in nonintrusive load monitoring using steady-state and turn-on transient energy algorithms. In: Computer Supported Cooperative Work in Design (CSCWD), 2010 14th International Conference on: IEEE; 2010. p. 27-32.
15. Shrestha A, Foulks EL, Cox RW. Dynamic load shedding for shipboard power systems using the non-intrusive load monitor. In: Electric Ship Technologies Symposium, 2009. ESTS 2009. IEEE, 20-22 April 2009; 2009. p. 412-9.
16. Ninad Khandekar NP, Kalpak Thube and Dr. P. B. Mane. Non-Intrusive Appliance Load Monitoring System Using Zigbee Protocol. International Journal of Engineering Research & Technology (IJERT) April 2014;3(4).
17. Semwal S, Shah G, Prasad R. Identification residential appliance using NIALM. In: Power Electronics, Drives and Energy Systems (PEDES), 2014 IEEE International Conference on: IEEE; 2014. p. 1-6.
18. Valero Pérez MN. A non-intrusive appliance load monitoring system for identifying kitchen activities. 2011.
19. Nasir HJA, Ku-Mahamud KR. Wireless Sensor Network: A Bibliographical Survey. Indian Journal of Science and Technology 2016;9(38).
20. Svozil D, Kvasnicka V, Pospichal J. Introduction to multi-layer feed-forward neural networks. Chemometrics and intelligent laboratory systems 1997;39(1):43-62.
21. I. Abubakar, S. N. Khalid, M. W. Mustafa, M. Mustapha, Shareef H. A NEW CALIBRATION METHOD FOR ZMPT101B VOLTAGE SENSOR MODULE FOR ACCURATE LOAD MONITORING. In: 6th International Graduate Conference on Engineering, Science & Humanities (IGCESH 2016); Universiti Teknologi Malaysia. 2016; 17th August, 2016. p. 112-5.