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Non-Intrusive Load Monitoring using Artificial Neural Network

Muhammad Zubair Salahuddin Chishti [1]

[1]Asia Pacific University of Technology and Innovation, Technology Park Malaysia, 57000, Kuala Lumpur, Malaysia

ABSTRACT

The project has been taken to perform research on Non-Intrusive Load Monitoring (NILM) using Artificial Neural Network (ANN) algorithm. For training ANN, Backpropagation Lebvenberg Marquardt (LM) algorithm have been employed instead of Backpropagation Gradient Descent (GD) due to its prediction accuracy of 87.2% for sixteen different switching combinations of 4 loads. The developed system uses interactive GUI to monitor real-time energy consumed by the loads every second. The load disaggregation technique for detection of sixteen possible occurrence of four load's events has been suggested as a suitable way of implementing NILM. The achieved prediction accuracy for the research gives, practically, a good fit countering the adverse effect of overfitting experienced in achieving high prediction accuracy in AI algorithms.

Type of Paper: Conceptual.

Keywords: Non-Intrusive; Artificial Intelligence; Simultaneous Load's Events; Internet of Things

1.Introduction

In the present era, energy crisis becomes an important issue for many industries throughout the world. Energy efficient devices such as LED lamps have greatly hit the market in reducing overall energy usage. Government awareness programmes have also been established along with the standards to inform the users on how to use electricity effectively and to reduce demand factor of a town or a region. Among these measures of solving energy crisis, Energy auditing tracks the energy flows in house, buildings or industries. It is a process by which the power drawn by the system is analysed, and the losses are estimated for each device. It highlights the potential cost saving opportunities at consumer's end as well (Govmu, 2013). For energy auditing, the conventional method of load monitoring in an energy audit, requires sensors, which are attached to each load and monitors the corresponding energy consumed by the load.

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* Corresponding author:
E-mail: zubair_chishty@live.com
Affiliation: School of Electrical & Electronic Engineering Universiti Sains Malaysia Penang, Malaysia

This is termed as intrusive load monitoring and is time consuming and ineffective. In contrast to it, Non-Intrusive Load Monitoring (NILM) is an effective approach * Paper Info: Revised: February 2018 to load monitoring systems. It disaggregates loads from the main Distribution Board (DB) resulting in an effective use of sensors. The idea itself was enunciated in 1980's by Hart and has gone through several evaluations in conjunction with technological advancements per era.

NILM outperforms the state-of-the art methods of load monitoring with respect to cost and time. Since machine learning algorithm have been proven to be efficient in differentiating patterns from disaggregate data (Laughman et al., 2003), therefore ANN, branch of semi supervised machine learning has been employed for developing NILM system. In addition to it, Singh & Majumdar (2017) discussed that sparse coding technique of deep learning can achieve a maximum accuracy of 76% for recognizing the loads from the main utility and suggested using ANN to enhance the accuracy of the system up to 80% or more.

2. Literature Review

Power signatures constitute the essence of NILM system, as it tracks the distinctive features of a load. The very first NILM system, developed by Hart in 1985, used steady state characteristics as a power signature. The steady state characteristics involve monitoring the real and reactive power of the system based on occurrence of load's events. Later, Sultanem (1991) utilized the transient as the power signature for load detection and evaluated that the resistive loads are not untraceable solely by the transient power signature due to very small transient of resistive loads. Some of the recent research (Zhao, L. Stankovic & V. Stankovic, 2016; Baets et al., 2017), casts the load's switching event as a feature to improve load disaggregation.

Since real and reactive power are additive as compared to transient which is not additive. Hart uses Switch Continuity Principle (SCP) to assume that only one load is turned on at a time. Makonin (2016) tested this assumption and found out that assumption of 4% simultaneous change in power supplies had been changed to 20.8% especially for a home with large appliances. Sultanem (1991) classifies each load as resistive, inductive or capacitive and discuss their corresponding significant power signatures. In later research the traditional steady state features (P, Q and power factor) and transients (turn on transient, current harmonics) were combined to beneficiate NILM. Chang, Lin & Yang (2008) and Chang et al. (2011) both took steady state (P & Q) and transient state (turn on transient Ut) as the power signature. The later one suggested that using the transient feature one can also tell the physical properties of the load. This could aid in checking the fault in the power system without personally checking the generators. The phenomena was also confirmed by Mostafavi & Cox (2017), recently. Thokala, Chandra & Nagasubramanian (2016) utilized the rise and fall steady state feature, operation time and raw signal to monitor the switching cycles of an appliance.

AI is the key to NILM, however, the prediction accuracy of the system decreases as the number of loads increases.The prediction accuracy or recognition rate is the ratio of developed system predictions to the actual results (Kattan, Abdullah & Geem, 2011). Janani & Himavathi (2013) achieved the maximum accuracy of up to 96% but does not show simultaneous recognition of 8 loads at the same time. Instead, the loads were broken down into smaller chunks and then accuracy of the system was evaluated, under these circumstances cascade architecture taking 0.5% precedence over feed-forward architecture of NN becomes questionable. Chang et al. (2016) reported accuracy of 80.42%. The developed device could differentiate an old device from a new one from a set of six appliances each having its new and old counterpart. Semwal, Shah & Prasad (2014) despite achieving accuracy of 99.18% in load disaggregation using ANN uses only transient power signature, which can limit its use for purely resistive loads. Chang, Lin & Yang (2008) claimed to achieve almost 100% accuracy with ANN but only tested two sets, one for 3-phase 220V loads and one for single phase 110V loads. Each set contains three loads and did not detect these loads collectively. Rather the paper evaluates the individual accuracy for each class. Chang et al., 2011 also got the same results with three different loads in multiple sets but same as previous research doesn't combine the loads, to evaluate overall recognition rate. In Gonçalves, Ocneanu & Bergés (2012) & Shao et al. (2013) high power loads were successfully recognized but their system has limitation for detecting the low power loads being a major drawback in unsupervised machine learning algorithm. Nardello, Rossi & Brunelli (2017) achieved an accuracy of 89% for 5 individual detection of loads but also could not performed it collectively. Zhao, L. Stankovic & V. Stankovic (2016) manage to get prediction accuracy of 77.2% with their proposed graph signal processing method but the technique could not be realised in real-time.

The core reason of employing ANN is its capability of detecting non-linear functions. Moreover, ANN is adaptive to diverse environments and has high noise tolerance (Janani & Himavathi, 2013).

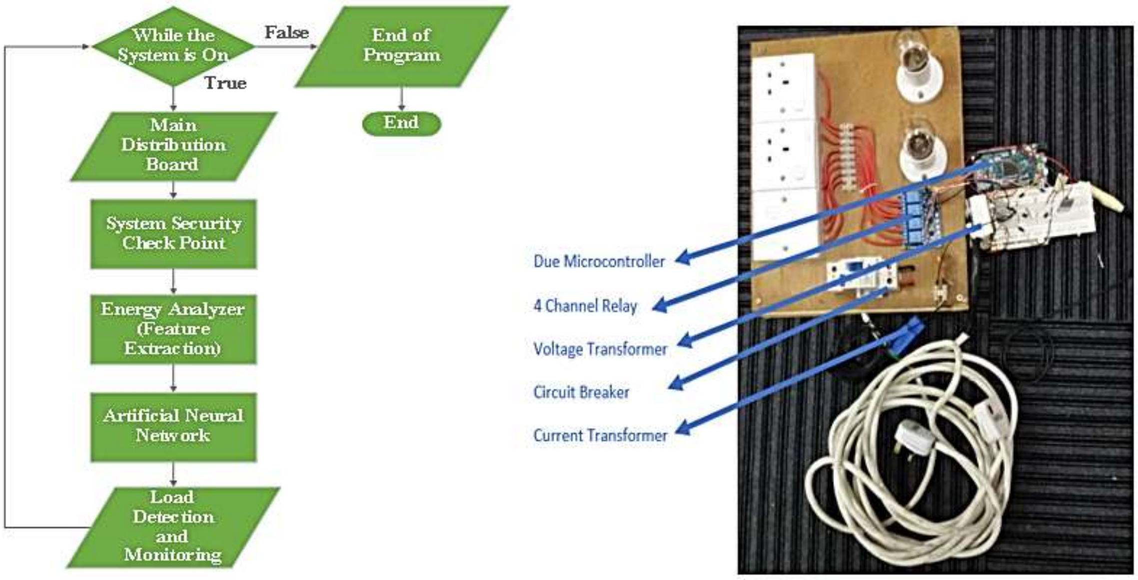
3. Methodology

The flowchart, shown in Figure 1(a), describes the system flow of the pre-trained ANN model using LM algorithm. The real-time system involves a security checkpoint following the DB to ensure the system has been accessed by an authorised personal. The energy analyser, then took real-time data from DB and extracts its features, which is then sent to ANN model resulting in an instantaneous load detection.

3.1 Concept Design

Since temperature is the main factor that changes with surroundings specially in Malaysia. Due to this reason, the temperature has been assumed to be constant to simplify the design equations. Also, the losses in energy analyser has been assumed to be negligible due to low current rating of Arduino Due Microcontroller. For the development of DB, Suruhanjaya Tenaga (2008) suggested to use 1.5 mm2 gauge wire for lighting loads (Incandescent bulbs) and 2.5 mm2 for socket outlets (Panasonic Blender and LED Floodlight). The circuit breaker ratings had been suggested to be 40 A. TBC circuit breaker was used as it has gone through QC test.

The most important design component in NILM is the energy analyser. As aforementioned microcontroller only accepts positive voltage from 0-3.3 V, due to which an offset circuit was added in its configuration such that the peak to peak ac wave from CT and VT falls under the aforementioned range. The ac voltage from VT is further stepped down to give 2.3 V peak to peak as shown in Figure 2. The offset is given by the same microcontroller and to reduce ac ripples in it, the capacitor was added in parallel. In this way, the ac ripples in the offset, seeing capacitor as a lower resistance, flows through it whereas dc component of the voltage securely gives the desired voltage of 1.65 V, since dc current treats capacitor as an infinite impedance. The given offset's value centralizes an ac waveform in the microcontroller's analogue voltage range. Equation 1 calculates capacitor's value ensuring its reactance to be lower than the voltage divider resistance, used for getting desired offset voltage.



(a) (b)

Figure 1 Proposed NILM Methodology (a) and Hardware Implementation (b)

$$C = \frac{1}{2\pi f X_c} \quad (1)$$

Where,
X_c = Reactance of a capacitor,
f = Freqeuncy,
C = Capacitor’s value.

Total ten features were employed for load disaggregation. Data acquisition was carried out via USB using Arduino IDE at a sampling rate of 2.7 kHz. ‘Emonlib’ open source library calculates real power and power factor as the first two features for load recognition. The calculated features and sampled ac waveforms from Arduino IDE is then sent to MATLAB® for processing in packets of 1024 samples. In MATLAB® the remaining eight features were extracted by taking eight peak values of load’s harmonics using Fast Fourier Transforms (FFT). All these features were stored in a matrix as column. For each load’s event, total 500 rows of ten features were used, resulting in a training data set of 8000 rows for sixteen classes of load’s event as shown in Table 1. MATLAB®’s Statics and Machine Learning Toolbox was used for combined training and testing of ANN model in the ratio of 7:3, respectively.

Table 1 Truth Table for Simultaneous Occurrence of four Load’s Events

Load States	LED Floodlight	Panasonic Blender	Incandescent Lamp Two	Incandescent Lamp One
1	0	0	0	1
2	0	0	1	0
3	0	0	1	1
4	0	1	0	0
5	0	1	0	1
6	0	1	1	0
7	0	1	1	1
8	1	0	0	0
9	1	0	0	1
10	1	0	1	0
11	1	0	1	1
12	1	1	0	0
13	1	1	0	1

14	1	1	1	0
15	1	1	1	1
16	0	0	0	0

3.2 Constructional Details

Figure 1(b) deploys the hardware implementation of the project and the following Figure 2 shows the entire circuitry for the constructional development of NILM project.

4. Results

With backpropagation LM approach of training ANN the simultaneous load's event detection was done with an accuracy of 87.2 %. However, by using backpropagation GD model the accuracy was decreased to 80% making the former algorithm appropriate for NILM training examples. Figure 3(a) shows the overall ANN confusion matrix collectively trained and tested by using backpropagation LM model. Moving forward, Figure 3(b) displays the GUI for system's security program addressing an ethical issue with NILM as pointed out by Hart (1985). Finally, Figure 3(c) demonstrates the GUI for real-time load detection.

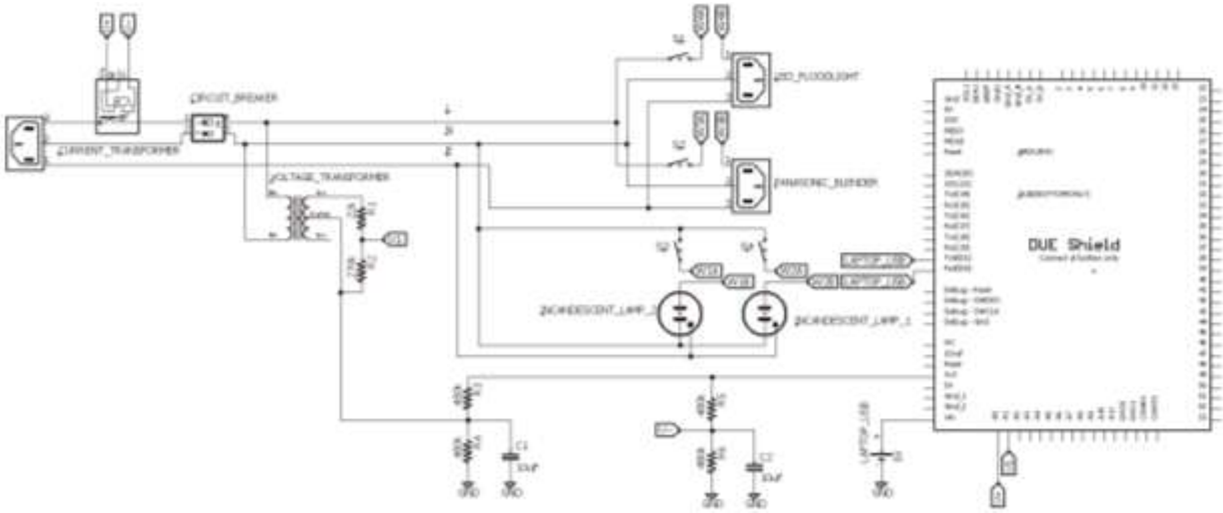
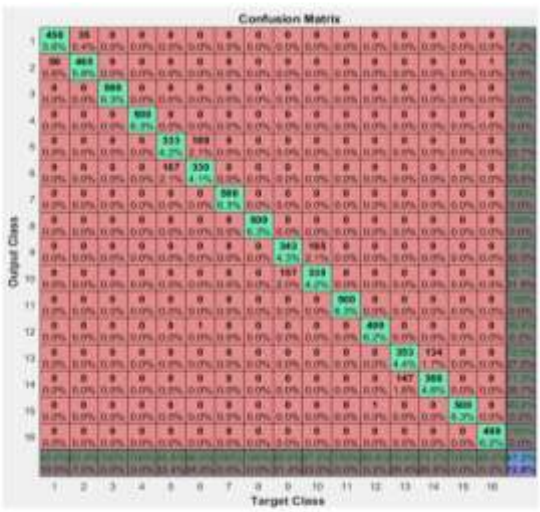


Figure 2 NILM System Schematic



(a)

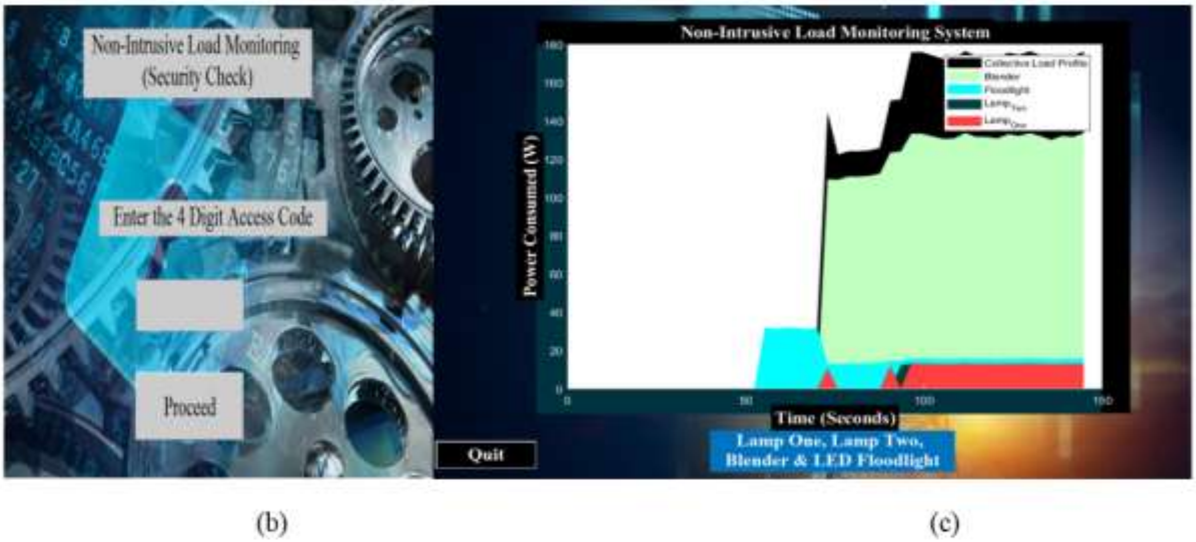


Figure 2 Confusion Matrix (a), Security Program GUI (b) and Real-time Load Disaggregation GUI of the Project (c)

5. Discussion

The developed NILM project, further its research in online energy monitoring along with detection of simultaneous occurrence of load's events. LTSpice simulation was used to confirms the designed offset circuit of energy analyser. Multimeter and digital oscilloscope were employed for practically testing and analysing waveforms from CT and VT. In social aspects of sustainable development, the project has an easy to use interface. The online monitoring provides ease of access to its user. Load profiles of a house or any residential or commercial buildings can be developed with convenience using NILM system. Moreover, the project can be used for human activity monitoring for elderly patients by the doctors to provide immediate help in case of emergency. In industrial zone, the developed system could help in tracking the machines consuming more reactive power than active power and helps saving the power system from overloading. In addition to it, the developed system cost under RM 1000 giving margin of up to 6 months maintenance in case of any damage to the sensors or the system. Also, the security program incorporated in the system takes the GPS coordinates, location and area from where the system is being accessed and email them to the product administration by using IP address saving cost on GPS sensor. Moreover, the system blocks the access after three consecutive entry of wrong password ensuring complete safety of the system from theft.

Additionally, environmental consideration has also been addressed in NILM system. Being able to monitor power consumption of the loads, a person can effectively monitor unnecessary loads being turned on and can effectively corners the loads consuming more power on a daily basis. This would inform an individual to limit use of such loads or to replace them with new energy efficient loads. If the same measure is carried out by an entire town, it results in a major reduction in demand factor of the area, saving the natural resources being used by electric utility companies. In Malaysia, the measure can help in reducing the use of coal being one of the main element used for electricity generation according to the newspaper The Star Malaysia (2017), saving the adverse effects of carbon dioxide emission to ozone layer. Saving ozone layer reduces the effects of global warming and goes back to the reduction in operating air conditioners, thereby, completing the energy cycle of the project.

6. Conclusion

In conclusion, the developed NILM system successfully achieved an accuracy of more than 80% as suggested by Singh & Majumdar (2017). In addition to it, the system disaggregates sixteen-simultaneous occurrence of four load's events effectively, creating an easy solution of developing residential or commercial load profiles. The IoT feature in terms of system's security program enable its safety from theft. The online monitoring feature facilitates an individual in monitoring loads from anywhere in the world. The research in the field of NILM is important as it aids in addressing energy crisis in the world. The project can include further diversified loads and control in its schematic, making NILM an absolute gate to the implementation of smart home technology.

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