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The smart meter design for total waste of electricity usage costs on household sector calculating using artificial neural network method

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Abstract. This research proposed a Smart Meter design that have a feature to calculate the total wasted energy from electricity usage. This feature obtained by monitoring and scheduling any installed electricity equipment. With this feature, every Smart Meter user expected to be able to manage the use of electronic equipment that installed in each home optimally. In this research artificial neural network with a radial basis network learning algorithm (RBFNN) used to identify any connected device. This method is one of the controlled learning methods and have fast learning speed. To identify the electronic equipment, it used the RMS current rating and the peak value of the wavelet transformation of the RMS current. From the transformation will become input for the RBFNN. Experiment and simulation results show that the Smart Meter with radial basis network method able to identify each load well, where the average training accuracy is 96.76% and the average testing accuracy is 85.08%.

1. Introduction

Today, energy conservation is a challenging issue as it exponentially increases energy demand. Fossil energy resources are limited and estimated global energy demand will doubled by the end of 2030 [1]. The economy, climate change, and energy crisis in a country are directly affected by the growth of energy consumption. Steps to reduce electricity wastage can be achieved by monitoring the electricity consumption and relaying back the information to the consumer [2].

Several studies have shown that maximum electrical energy savings can be achieved using a direct feedback mechanism providing electrical energy usage real-time information [3]. In the future, the load monitoring system will focus on strategy development techniques to minimize the amount of instrumentation equipment using the Non-Intrusive Load Monitoring (NILM) system [4]. Several methods have been used to identify loads based on transient conditions using wavelet transforms and steady state conditions that use Fast Fourier Transforms, with artificial intelligence methods that have multi-layer perceptron classification capability, basis radial function, and support vector machine, in real time [5].

This research proposes a smart meter simple concept with one monitoring sensor and identification of electric energy consumption in household sector by utilizing current waveform from every electronic equipment. The load identification process will be done using radial basis network method in real time. The concept of the smart meter offers a low-cost technology but has more features than
analog and digital kWh meters installed in consumer house, such as: Details of total loads used by electric energy users, total cost of electricity usage, and total wasted energy from electricity usage.

2. Literature Review

The NILM system requires only sensors voltage and current, and this sensor not installed at each load. These sensors transmit information on the use of electrical energy for home energy management systems for monitoring and load control. Through this technique, the energy usage of each load can be monitored and controlled [6].

The wavelet transform is a linear transformation that is almost like the Fourier transform. However, there is an important difference between wavelet and Fourier transform that the wavelet transforms allow the time placement of the different frequency components from the signal that given. Using the wavelet transform, the frequency information and timing information of the occurrence of that frequency on the signal can be determined by precision [7]. In this research, the signal of the simulation will transform from time domain to frequency domain using wavelet transformation, on simulation we use wavelet transformation tool box in LabVIEW, and we use the signal for the input of transformation. The peak of signal wave of the result from wavelet transformation is use as the parameter in the input of radial based network.

The neural networks with a radial basis is the learning algorithm that supervised and requires more neurons compared to feedforward networks. This network works well if the input data quite a lot. In this basis radial network, the inputs of the vector distance between the weight vectors and the input vectors multiplied by the bias weights will be processed using radial-based activation functions. While in the output layer, Purelin activation function will be used [8]. Training algorithm of the radial basis network is a feedforward stage. There are two input for neurons, first is root mean square current and the second is peak value of wavelet transformation. While the neuron output affirms the electronics equipment status. The identification status of electronics equipment is a neuron output labelled by binary numbers (0 and 1). Neurons in a single hidden layer used for all different electronics devices that connected in the house. The number of these neurons depends on the amount of training data. The more training data used, the output data will be better due to the complexity of mapping factors on inputs and outputs on every electronic equipment.

In this study, the radial basis network used as a method to identify load names and the combinations of electronic equipment on and off status conditions based on real time load data measurement. The training progress of radial basis network is using MATLAB software with input and output parameter that we get from wavelet transformation.

3. Research Method

3.1. General Structure of Load Identification

The general structure of the load identification system shown in figure 1. The main parameters used in load identification systems are voltage and current wave samples. Measurement of the current in system identification can be performed by measure the currents on each single load separately. This method requires a relatively high cost because the current sensor installed on each load.

![Diagram](image.png)

**Figure 1.** General Structure of load identification.

The data acquisition module serves to obtain the measurement signal under steady state and transient conditions. Sampling frequency to obtain signals in steady state and transient condition
regulated through data acquisition module. The event detection module will detect if any load is active or inactive. In addition, this module is also applied to decide whether the load is connected to the system or released from the system. If the load is connected, the sample shapes of the voltage and current waves will be analysed by the load identification module. In the subsequent process, the identified load information sent to energy management for the evaluation of the energy wastage rate.

3.2. Load Identification Method
Methods for monitoring and identifying loads specified into two categories that are method under the steady-state and the transient conditions. The method under steady state conditions uses a constant signal parameter when the electrical load operates in a stable state. While the method in transient conditions relies on transition switching signal parameter from the load. A method that applied to identify the load is the method based on the waveform characteristics [9]. In addition, the peak current characteristics, base current, and RMS current (root mean square) can be used as the parameters of the load identification.

3.3. Schedule of Each Home Appliance
In this study, 4 equipment is used, there are blender, hairdryer, LED lamp 11 Watt and ETL Lamp 35 Watt. Each equipment will pass through the several same processes with previous process: Measuring the RMS wavelet current in each equipment, wavelet Transform of current wave in each equipment, training using radial basis network, testing several LABVIEW feature that already designed. The data sample and schedule can be seen in table 1 and 2.

**Table 1.** Sorting of radial basis network sample data appliance.

| No. | Electronic Device Combination | Amount of Training Data Sample | Amount of Data Sample Testing |
|-----|--------------------------------|--------------------------------|-------------------------------|
| 1   | Blender                        | 3                              | 2                             |
| 2   | Hairdryer                      | 3                              | 2                             |
| 3   | LED Lamp 11-Watt               | 3                              | 2                             |
| 4   | ETL Lamp 35-Watt               | 3                              | 2                             |
| 5   | Blender + Hairdryer            | 3                              |                               |
| 6   | Blender + LED lamp 11-Watt     | 3                              | 2                             |
| 7   | Blender + ETL Lamp 35-Watt     | 3                              | 2                             |
| 8   | Hairdryer + LED Lamp 11-Watt   | 3                              | 2                             |
| 9   | Hairdryer + ETL Lamp 35-Watt   | 3                              | 2                             |
| 10  | LED Lamp 11-Watt               | 3                              | 2                             |
| 11  | Blender + LED lamp 11-Watt     | 3                              | 2                             |
| 12  | Hairdryer + ET L Lamp 35-Watt  | 3                              | 2                             |
| 13  | Blender + LED lamp 11-Watt     | 3                              | 2                             |

**Table 2.** Schedule of each home.

| Equipment   | Working time       |
|-------------|--------------------|
| Blender     | 10.00 am – 01.00 pm|
| Hairdryer   | 07.00 am – 09.00 am and 03.00 pm – 05.00 pm|
| LED Lamp 11W| 05.00 pm – 06.00 am|
| ETL Lamp 35W| 05.00 pm – 10.00 pm|
4. Analysis & Results

| ETL Lamp 35-Watt | Hairdryer+ LED lamp 11-Watt + ETL Lamp 35-Watt | Blender + Hairdryer + LED |
|------------------|-----------------------------------------------|-----------------------------|
| 14               | 3                                             | 2                           |
| 15               | 3                                             | 2                           |

Figure 2. Current Root Mean Square Plot Result Lamp Appliance ETL 35 watt.

Figure 3. Current Root Mean Square Plot Result Blender Appliance.

Figure 2 show the simulation result of RMS current from Energy Thrift Lamp (ETL) 35 Watt, it shows that the RMS current of ETL 35 watt is around 150 mA. Figure 3 show the simulation result of RMS current from blender, it shows that the RMS current of blender reach up to the same point about 1 A.

Figure 4. Current Root Mean Square Plot Result Hair Dryer Appliance.

Figure 5. Current Root Mean Square Plot Result Lamp Appliance LED 11.

While figure 4 show the simulation result of RMS current from hair dryer, it shows the RMS current of hair dryer is about 1 A to 1.2 A. It shows that the result of RMS current from ETL 35 watt is under from blender and hairdryer. Figure 5 show the simulation result of LED 11 watt, it shows that the RMS current from LED 11 is at the same point at 50 mA, it is under the result of ETL 35-Watt simulation.

The result of weight and bias that we get from radial basis network training with MATLAB will send to LabVIEW. In this progress, training is not required, smart meter that we designed can identify blender, hair dryer, ETL 35 watt, and LED 11 watt.
Table 3. Load Identification Result for Mixed Electronics Appliance.

| No | Electronic appliance combination | Training Accuracy (%) | Testing Accuracy (%) | No | Electronic appliance combination | Training Accuracy (%) | Testing Accuracy (%) |
|----|----------------------------------|-----------------------|----------------------|----|----------------------------------|-----------------------|----------------------|
| 1  | Blender                          | 100                   | 78.86604 131         | 9  | Hairdryer + ETL 35 Watt          | 100                   | 68.05964 07          |
| 2  | Hairdryer                        | 100                   | 76.81270 273         | 10 | LED 11 Watt + ETL 35 Watt        | 100                   | 91.06881 559         |
| 3  | LED 11 Watt                      | 100                   | 97.79629 975         | 11 | Blender + hairdryer + LED 11 Watt| 100                   | 84.22691 221         |
| 4  | ETL 35 Watt                      | 100                   | 99.01986 32          | 12 | Blender + hairdryer + ETL 35 Watt| 100                   | 80.61592 912         |
| 5  | Blender + Hairdryer              | 100                   | 91.56898 881         | 13 | Blender + ETL 35 Watt + LED 11 Watt| 100                   | 73.40062 406         |
| 6  | Blender + LED 11 Watt            | 100                   | 78.23230 885         | 14 | Hairdryer + ETL 35 Watt + LED 11 Watt| 100                   | 87.93839 088         |
| 7  | Blender + ETL 35 Watt            | 100                   | 63.65545 735         | 15 | Blender + hairdryer + LED 11 Watt| 100                   | 95.11031 818         |
| 8  | Hairdryer + LED 11 Watt          | 100                   | 81.71946 239         |     |                                  |                       |                      |

The result of the radial basis network training can be seen in the table 3. The radial basis network is able to identify the load well. From the accuracy of trial and training also given in table 3. Whole electronic device that we try, the features of trial from smart meter and the detail energy waste application can be seen at figure 6, figure 7 and figure 8 below.

Figure 6. Smart Meter Indicator.

Figure 7. Electrical Energy Usage and Billing Actual Measure.

Figure 8. Detailed Waste Energy Usage Interface.
5. Discussion & conclusion
Radial basis network is used to identify the load at real time for smart meter application. From the experiment analysis, it can be conclude that the purposed method is faster than backpropagation neural network for the computation training and testing work speed. The accuracy of training and testing using radial basis network show that the method is identify the load at real time with 100% accuracy average for training and 83.2 % accuracy average for testing. By utilizing the RMS data and the peak value of wavelet transformation from each electronic device as input in radial basis network show the good reliability. It can be seen from testing analysis from the variety of voltage at different level, the changes of power consumption and different load operational. Next research step is wavelet transformation RMS current as parameter to identify electronic device or load.

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