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Hybrid Method of DFT and Constructive Backpropagation for Energy Monitoring

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Abstract: This study present new technique to identify similar signal of appliance such as the same brand and the specification of appliance. The proposed method was develop in the study was converting signal RMS current of appliance from time domain to frequency domain. To distinguish similar signals foureir transformation was conducted to result low frequency which represent of appliance. And then Constructive Bcak Propagation-Neural Network (CBP-NN) was employed for decision making of identification. The CBP-NN was designed using five input and two output. The experiment result shown that the method working properly with very small, i.e., error 0. 0659% for case 1 and 0. 2797% for case 2.

Key words: Time domain, frequency domain, low frequency, constructive back propagation, smart-meter, employed

INTRODUCTION

Now a days, presentation of electric data transaction in detail and complete has become imperative to reduce potential conflicts that may arise from customers. So that, power companies should start changing transaction recording device from the conventional to modern one, which is able to record electricity usage in detail as the transaction time, duration of use and cost (Benzi *et al*., 2011; Erkin *et al*., 2013).

The concept of smart-meter which is proposed in this study is a part of Non-Intrusive Load Monitoring (NILM) concept which has developed by many researchers in the world. Norford and Leeb (1996) have developed nosn-intrusive electrical load monitoring in commercial building based steady state and transient load detection algorithm. Figueiredo *et al*. (2012) have developed a load detection entrance (turn-on)and load out (turn-off) as well as by extracting the signal into a signal of active power, reactive power signal and power factor, this method is quite complicated. Chang *et al*. (2012) have developed Non-Intrusive Load Monitoring (NILM) based on transient signal signature and use Digital Wavelet Transformation (DWT) as a decomposition method. Chang *et al*. (2012) also employing Neural Network (NN) as method to make decision for identification of appliance.

In other hand, Back Propagation Neural Network (BP-NN) method (Chang *et al*., 2012) also have applied to many kind of identification systems but the BP-NN usually has problem with training process (Gunaseeli and Karthikeyan, 2007; Sharma, 2010). So that, many methods were developed to improve it such as Constructive Back Propagation Neural Network (CBP-NN) (Gunaseeli and Karthikeyan, 2007; Sharma, 2010). CBP-NN also has been succesfull applied to solve many engineering problems (Srinivasan *et al*., 2006; Aquino *et al*., 2010; Abdelwahab and Abdel-Aty, 2002; Syai'in and Soeprijanto, 2010; Syai'in *et al*., 2011, 2012; Dieu and Ongsakul, 2007).

In this study will develop a prototype of smart-meter (kWh-m) that able to record power consumption in detail including type appliance and time use. Basically, any electrical appliances have unique characteristics of transient signals. It is just like a fingerprint identification in attendance machine. The proposed method using peak value and steady state value which is improvement of (Norford and Leeb, 1996) as identity of appliances and combining with CBP-NN (Gunaseeli and Karthikeyan, 2007; Sharma, 2010) as a decision method. The advantages of the proposed method is it can detect appliance easily and construct number of neuron automatically during the training process. So that, it can reduce the time consuming in training process.

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The advantages of smart-meter proposed in this study is it's capability to detect devices that have the same brand and specification. That it has not been done by previous researchers (Basu *et al*., 2015; Syai'in *et al*., 2014) which only detect different appliance.

MATERIALS AND METHODS

To improve performance of smart-meter (Syai'in *et al*., 2014) in identifying similar appliance which are appliances with the same brand and the same specification. The fourier transformation was applied to convert appliance's signal of appliance from time domain to frequency domain (Arrillaga and Neville, 2003). After that Constructive Back Propagation Neural Network (CBP-NN) is employed to cluster and identify it. Low frequence (1-5 Hz)of appliance's signal in frequency domain is used as input and the status of appliance (ON or OFF)is used as output.

The overall process of the proposed method is described in three steps as follows:

- The first step: signal conditioning
- The second step: signal transformation
- The third step: signal identification

Signal conditioning: In this experiment, smart-meter is installed at the electrical service entry for load disaggregation as shown in Fig. 1.

Smart-meter component consists of a current sensor, microprocessor-Arduino, SD-Card and a display screen, so, it can be operated stand alone without PC. The appliances used as loads are two Fan with the same brand and the same specification as shown in Fig. 2.

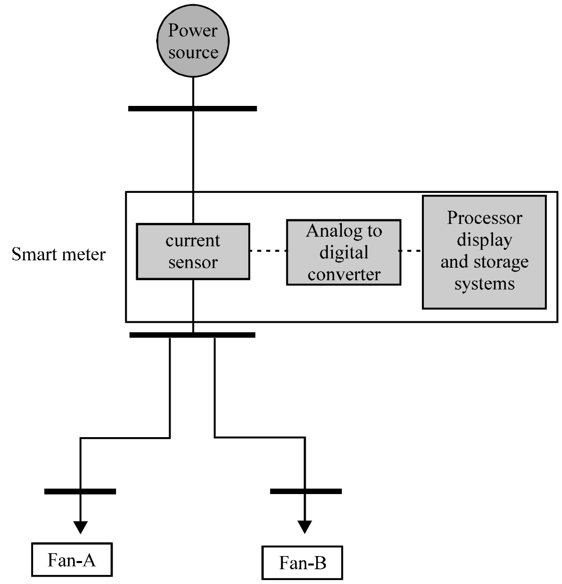

Fig. 1: Installation of smart-meter

Fig. 2: Experimental overview

Signals transformation: After signal conditioning process is conducted, the next process is signal transformation. The signal object was first observed is a transient phenomenon on RMS value of current that includes transient ON and transient OFF. An example of signal transient ON can be seen in Fig. 3.

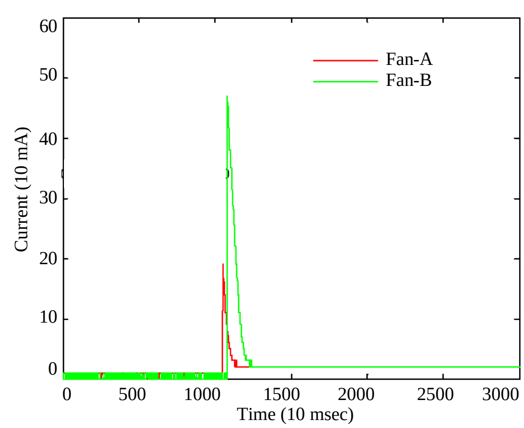

Fig. 3: Signal transient ON signal transient ON of appliance in time domain

Figure 3 shows signal transient ON in time domain of two Fan. The signals actually have similar pattern but different magnitude of peak value. Using fourier transformation (Arrillaga and Neville, 2003) signal in Fig. 3 is transformed to frequency domain and the result is provided in Fig. 4.

Figure 4 show there are no intersection of frequency magnitude both Fan. The same case also occur in signal transient OFF as shown in Fig. 5.

Figure 5 shows opposite pattern between Fan-A and B. In the signal transient ON Fan-B has magnitude bigger than Fan-A but in signal transient OFF Fan-B has

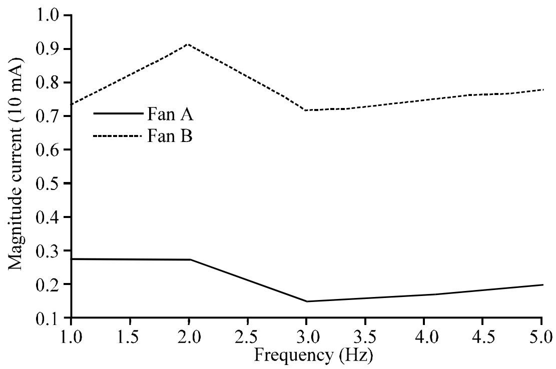

Fig. 4: Singnal transient ON which has converted to frequency domain

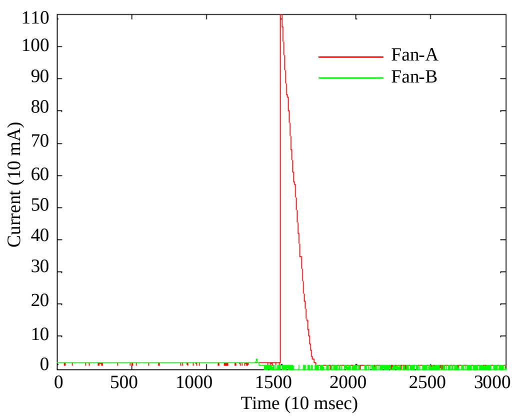

Fig. 5: Signal transient OFF. Signal transient ON of appliance in time domain

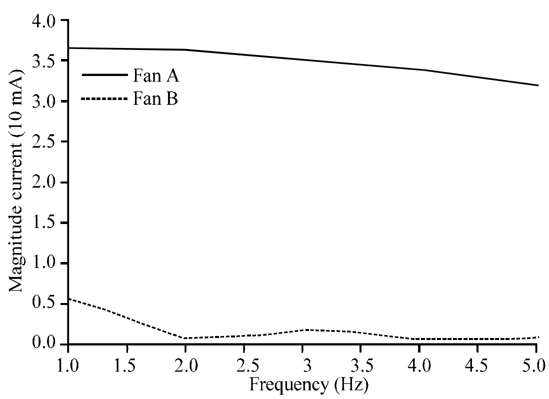

Fig. 6: Singnal transient OFF which has converted to frequency domain

magnitude smaller than Fan-A. The signal transformation of signal in Fig. 5 to be frequency domain can be seen in Fig. 6. Figure 6 also shown that there is no intersection of magnitude frequency 1-5 Hz.

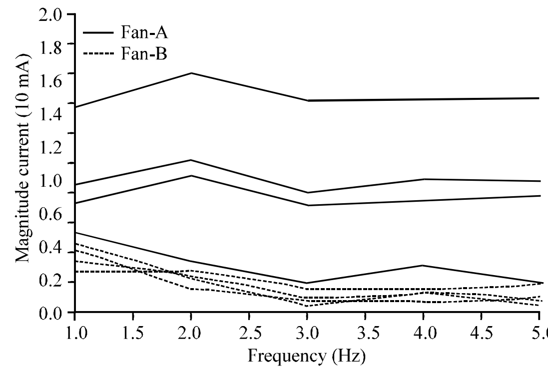

Fig. 7: Signal transient ON of data input. Signal Of appliance in frequency domain

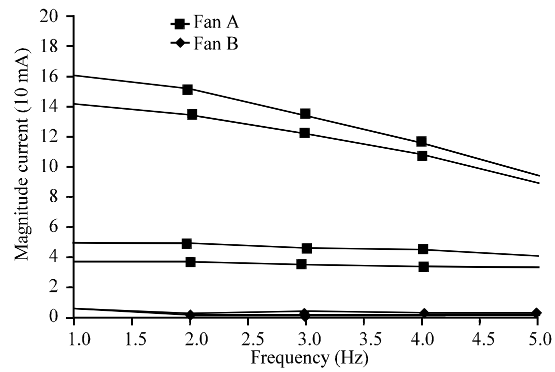

Fig. 8: Signal transient OFF of data input. Signal of appliance in frequency domain

Signal identification: To identify signal of appliances using CBP-NN, the three steps design need to process sequently. The first step is collecting data input and output. The second step is training process using constructive back propagation algorithm. And the third step is test the converge weight of neural network to verify the performance of identification.

The data used as inputs are magnitudes of frequency 1-5 Hz that were transformed from time domain. To conduct training process many samples data need to collect. In this process bumber of sampling data of appliances are twenty. But to make picture clear, only 4 data shown in the Fig. 7 and 8

Figure 7 and 8 show that frequency magnitude of Fan-A and B form cluster. That means the signal can be identifed easier by neural network.

The structure of neural network proposed in this study is expressed in Fig. 9. Figure 9 shows that the output of NN is status of appliance. And the number of neuron will determine automatically by CBP (Gunaseeli and Karthikeyan, 2007; Sharma, 2010; Syai'in *et al*., 2014)

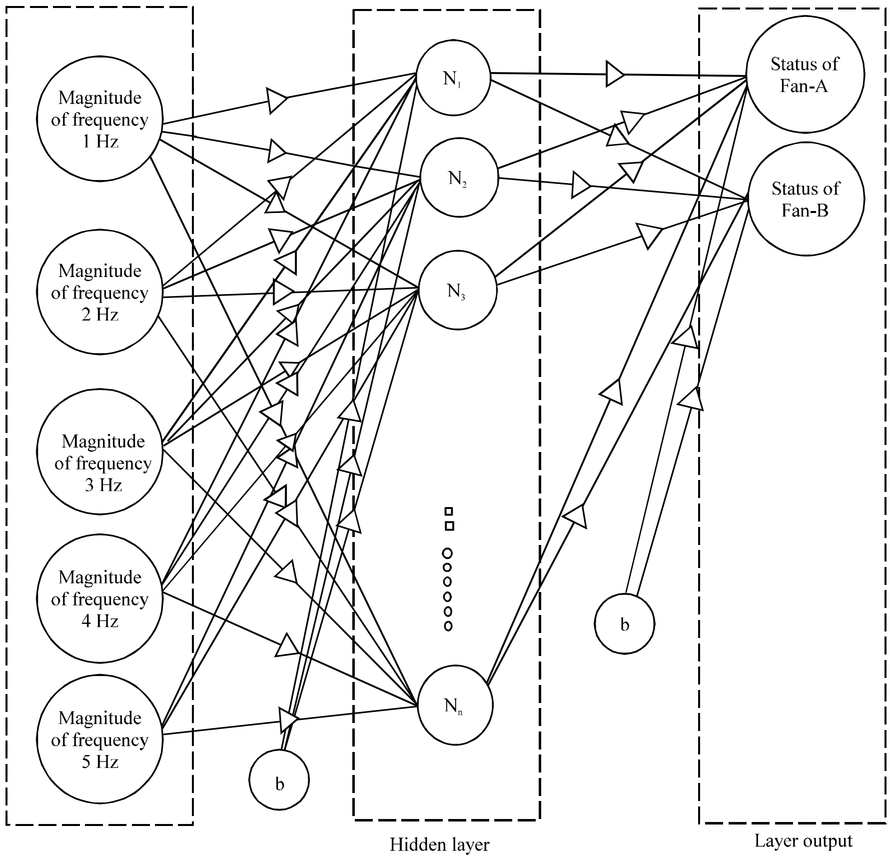

Fig. 9: Signal transient OFF of data input

method during training process, starting from small number. The converge trainning of CBP NN are two layer of hidden layer with number of neurons in each layer are 7.

RESULTS AND DISCUSSION

Simulation and data analysis: In this study, two fan that bought in the same time with the same brand and the same specification as Fig. 2 are operated as loads. And two cases also conducted to verify performance of the proposed method. The first case, fan is operated itself alone. And the second case, two fan are operated simultaneously.

Case 1; Fan is operated itself alone: The operation mode is Fan A turn ON and then turn OFF, after that fan B turn ON and then turn OFF.

For several experiment the result can be seen in Table 1. From Table 1, can be seen that the proposed method working properly in this case, the error of identification in this case is 0.0659% which is very small and if rounding off do in this case, it is mean the error can be ignore.

Table 1: Experiment result of case 1

Appliance operation		Monitoring by NN	
Fan-A	Fan-B	Fan-A	Fan-B
ON 1	OFF 0	0.9994	0.0005
ON 1	OFF 0	0.9995	0.0012
ON 1	OFF 0	0.9994	0.0005
ON 1	OFF 0	0.9985	0.0005
OFF 0	OFF 0	0.0012	0.0005
OFF 0	OFF 0	0.0005	0.0012
OFF 0	OFF 0	0.0005	0.0005
OFF 0	OFF 0	0.0005	0.0005
OFF 0	ON 1	0.0005	0.9994
OFF 0	ON 1	0.0012	0.9995
OFF 0	ON 1	0.0005	0.9994
OFF 0	ON 1	0.0005	1.0000
OFF 0	OFF 0	0.0012	0.0005
OFF 0	OFF 0	0.0005	0.0012
OFF 0	OFF 0	0.0005	0.0005
OFF 0	OFF 0	0.0005	0.0005

Case 2; Two fan are operated simultaneously: In this case the operation mode is Fan A turn ON and then Fan B turn ON after that Fan B turn off and then Fan A turn OFF The result of experiment can be seen in the Table 2.

Table 2: Experiment result of case 2

Appliance operation		Monitoring by NN	
Fan-A	Fan-B	Fan-A	Fan-B
ON 1	OFF 0	0.9894	0
ON 1	OFF 0	0.9795	0
ON 1	OFF 0	0.9994	0
ON 1	OFF 0	0.9895	0
OFF 0	ON 1	0	1.0000
OFF 0	ON 1	0	0.9992
OFF 0	ON 1	0	1.0000
OFF 0	ON 1	0	0.9985
ON 1	ON 1	1.0000	0.9985
ON 1	ON 1	0.9795	0.9995
ON 1	ON 1	0.9995	0.9895
ON 1	ON 1	0.9895	1.0000
OFF 0	OFF 0	0.0002	0
OFF 0	OFF 0	0	0
OFF 0	OFF 0	0.0008	0
OFF 0	OFF 0	0	0

From the Table 2 can be seen that the proposed method also can identify appliance very well with error tolerance 0. 2797%.

CONCLUSION

This study presents new technic based on trnasient signal conversion from time domain to low frequency domain that can improve accuracy of smart-meter to identify similar appliance. The experimental results demonstrate the validity of the proposed method. The proposed method potentially aid algorithms to enhance load identification.

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