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Domestic Load Identification with Single CT Using Artificial Neural Network

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ABSTRACT

Load identification technique using only single sensor are known as non-intrusive load monitoring (NILM) techniques which recognize the activity of downstream appliance/load by processing the data obtained by single monitoring sensor. The Domestic loads which are normally consuming single phase power supply, pusses a unique electrical characteristic for each, which are known as power signatures of the device. In this study, current signature has been chosen as turn on signature of the device & artificial neural network was trained from a single sample of each signature pattern for the different kind of loads. The trained neural network was then tested for deviation in supply line voltages as to determine the performance of the network. The test result shows that ANN is capable to handle such deviations and performs outstanding in load identification using single current transformer.

Keywords : artificial neural network, load monitoring, load signature, pattern reorganization.

INTRODUCTION

Conventional load monitoring system suggests each load to be monitored separately so as to determine the individual device state and time of any activity performed by user for the different kind of devices in premises. This method has always been too much expensive and very hard to implement especially when it comes to domestic load monitoring which is still facing a fusibility issue. In domestics there are hardly few scopes to wire the sensors to supervise the activity of the individual load as most of the supply distribution lines are bound to verity of loads and appliances. This infect makes it too much difficult to sense the individual device status. If we look forward to see the benefits of load monitoring along with views of energy conservation, demand management & energy audit, such information contains high-potential saving in energy by making unsupervised thing a supervised one.

A new method for load identification has been proposed in this paper which incorporate device's turn-on current signature as identification inputs to artificial neural network (ANN) for its pattern to be recognized. The method uses RMS current measurement samples obtained at relatively high sampling rate.

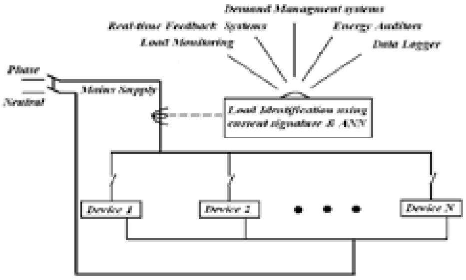

Figure a: Load identification overview

The determination of how much samples to be taken as input depends on largest no. of samples required to determine the final steady-state condition of the device. These samples are then treated as pattern/signature for training artificial neural network to classify the load by pattern reorganization. An overview of the proposed system has been shown in 'figure a' which shows its simple installation and leveraging applications. The main feature of the system lays in identifying each downstream loads using single current transducer, attached just after the incoming mains switch. Here current transducer act as an eye for ANN to observe, switching current signatures which than gets classified by trained neural network.

REVIEW OF PREVIOUS METHODS

The first nonintrusive load monitoring system was proposed by Gorge W. Hart [1] which had been a seminal work for further researches in the flow. He proposed load identification method which utilizes the steady-state information of power consumption of a loads being monitored. However this method latter found it's variants from different researchers to cope with many accuracy related issues. For example, the devices which gradually increase their consumption over a time it's very difficult to detect the edge of a step change in power consumption for the device. As said, it was a seminal work one of the recent method using smart meter data processing to determine the home appliance is presented in [2], which shows its accuracy 87% and feasibility using smart phones to influence household for their energy consumptions.

For more dynamic & reliable identification of load it is necessary to analyze dynamic response of electrical behavior when it is turned-on. Such response of electrical equipment is known as load signature for the device [3]. The load signature can be interpreted as appliance turn-on indication. The non-intrusive load monitoring using device's load signature can perform outstanding as it has more reliable information for a particular electrical load. An algorithm has been proposed to identify load by steady-state and turn-on transient energy [4].

Strategies for non-intrusive load monitoring have developed over the last 20 years [5]. The advances in computing technology makes it a new means of computational methods useful in practical, field-based NILM systems. The power signature study shows that there are many quantities which can be incorporated to make a reliable load identification method more robust then stead-state procedure. It is very much useful to construct the load signature database in order to study the taxonomy of electrical device to be identified [6].

SWITCHING CURRENT CHARACTERISTIC AS LOAD SIGNATURE

As the nature of domestic load, switching signature of a load current basically depends on the appliances electrical characteristics. It is very hard to find two identical switching characteristics between any of two devices, this is because of the components, used in manufacturing the devices cannot be identical. Hence we can easily use switching current signature as taxonomy for load identification [6]. Here in the method the RMS current is used with high sampling rate that can reflect device's electrical properties. As such whenever any device is turned-on it would be positive lift for RMS current value along with reflection of the device signature.

The mathematical illustration is as given bellow:

$$v_t = v_m \sin \omega t \qquad \text{…(1)}$$

Where is instantaneous voltage of supply line, is peak value of supply line voltage if we consider a load angle of device be the due to impedance z then corresponding instantaneous current will be and peak value will be as

$$i_t = i_m \sin(\omega t - \theta) \qquad \text{...(2)}$$

Now as discussed the RMS value of the current can reflect the signature of particular device if we calculate it with higher sampling of instantaneous current on considerable small interval between t_1 and t_2,

$$i_{rms}(t_{12}) = \sqrt{\frac{\int_{t_1}^{t_2} i_t^2 \, dt}{t_2 - t_1}}$$

The above equation shows continues time calculation which can be re written for sample interval k12,

$$i_{rms}(k_{12}) = \sqrt{\frac{\sum_{k_1}^{k_2} i_k^2}{k_2 - k_1}}$$

Here, k_{12} indicates the consecutive interval of samples.

As shown in Eq. (4) the value of irms will show the incremental current ramp and will reflect the load angle as it is being measured (we will visualize in the next section), will give the identical characteristic of the device.

SIMULATION OF LOAD SIGNATURE IN MATLAB

A MATLAB Simulink model can easily demonstrate the effect of Eq. (4) by simulating a single phase load being measured by rms current measurement block in 'powergui'. The voltage source of 325V peak with 50Hz frequency was utilized and measured the rms current values on discrete mode for sampling time t = 0.001s. the bellow figures shows the switching rms current signature for the different kind of loads simulated. For simplicity purpose the word 'current signature' is used instead of 'switching rms current signature'.

Device 1 which consumes 60w of active power, the current signature is as shown in figure 1.

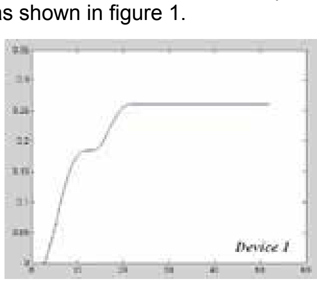

Figure 1: Current Signature for device 1.

Device 2 which consumes 500w of active power & 300W of reactive power, the current signature is as shown in figure 2.

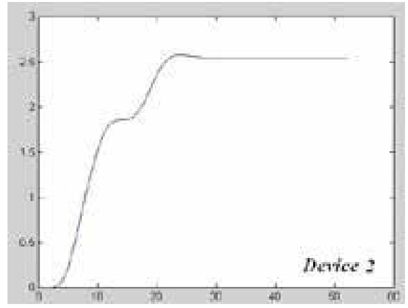

Figure 2: Current Signature for device 2.

Device 3 which consumes 250w of active power, 100W of reactive power and 2w of capacitive reactive power, the current signature is as shown in figure 3.

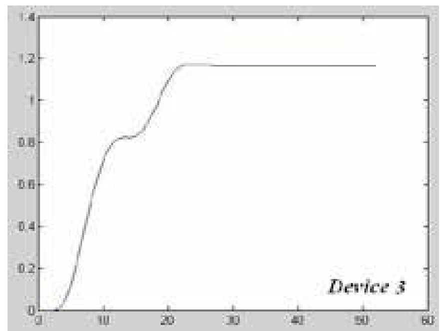

Figure 3: Current Signature for device 3.

Device 4 which consumes 1500w of active power 300W of reactive power & 50w of capacitive reactive power, the current signature is as shown in figure 4.

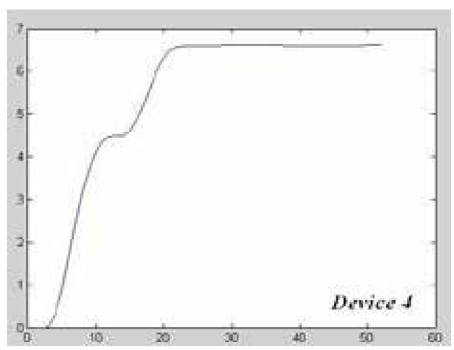

Figure 4: Current Signature for device 4.

As shown in the above devices current signatures reflects the corresponding trend when it is being turned-on hence these devices can be easily recognize if we can identify their pattern. The most suitable pattern reorganization tool for such kind of electrical property can be realized by artificial neural network which is described in next section.

TRAINING ANN BY INDIVIDUAL SIGNATURE

The training of artificial neural network was carried out in MATLAB using scaled conjugate gradient back-propagation algorithm [8]. The network automatically gets configured in using script with supplied input vectors and corresponding target-output vectors. Here in case of load identification, we must first have input output pairs to train ANN individually for current signatures for each device. The above figures 1, 2, 3 & 4 indicate that network should have nearly 50 samples as input and 4 corresponding output classes.

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The below figure shows, the plot of inputs consisting 48 samples of current signatures, for the 4 kind of loads.

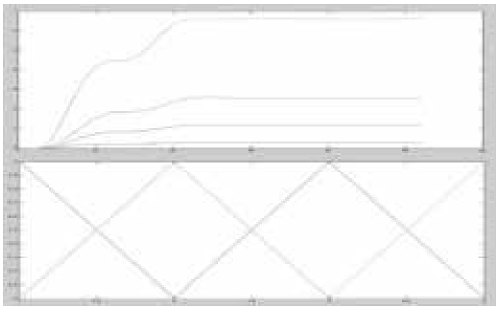

Figure 5 switching current signature for device 1, 2, 3 & 4

The bellow figure shows corresponding output class of signature i.e. 0001 0010 0100 1000 as plot.

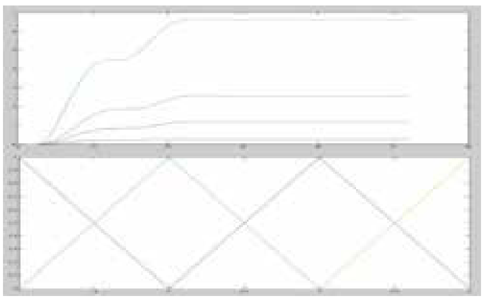

Figure 6: targeted output to train ANN for device classification.

The above set of pairs (input, output) was then used to train ANN with 4 hidden neurons in multilayer feed forward artificial neural network using SCG-BP method in MATLAB. The training statistics can be obtained using MATLAB command lines which show MSE (mean squared error) & gradient values at each epoch as shown in the figure 7 & figure 8.

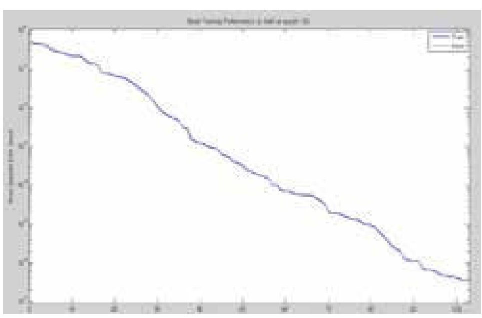

Figure 7 Training statistics MSE plot

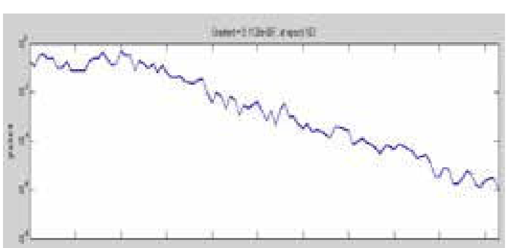

Figure 8: Training statistics - gradient plot

As shown in figure 7 & figure 8 the training of ANN had stopped at 103 epochs, when training conditions were satisfied. These two figures show the corresponding value of training statistics i.e. the values at every epoch. These plots are very useful at the time of training ANN with different no of hidden neurons which ultimately gives an idea about training state.

TESTING ANN FOR DEVIATION IN VOLTAGE

After ANN is trained it is ready to identify the load signatures, but it is very essential that the network be capable to recognize the switching current signatures even input has deviation due to some external factors. Here in the study ANN was tested for different peak voltage level to evaluate the performance of the network outputs. Bellow shown signature data was tested for doing that. 4 different peak value of voltage level were selected so as to simulate deviation. Total 16 input set was obtained with the same setup used as it was used for obtaining current signatures shown in figure 5.

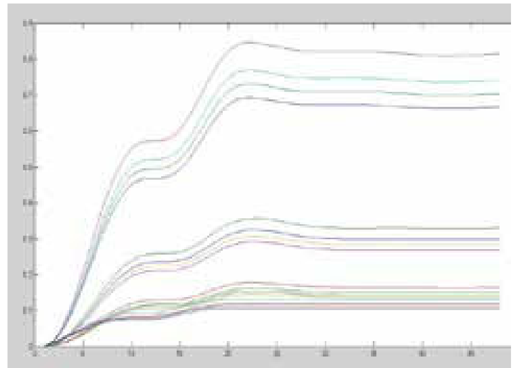

Figure 9: Current signature plots for deviation in voltage

Figure 9 shows the plot of 4 different current signatures for each type of loads. Which was used to test pre trained ANN for reorganization of corresponding device. The outputs were taken as the original 4 class for classification of devices as shown in figure 6.

TEST RESULTS

A. ROC (Receivers Operating Characteristics):

The ROC plot shown in figure 10 shows that the method used to identify the load, performs outstanding and recognizes the device correctly. The left hand side of the ROC plot shows true positive rate, as we already have indicated corresponding outputs related to deviated input to check whether ANN giving relevant indication or not. ROC plot can show the false positive rate of classification ANN if any of the input to network evaluated as different output then plot would shift to left-bottom. Hence we can say the deviation in input doesn't affect the classification done by the ANN which reflects a great feature of neural network to handle deviations.

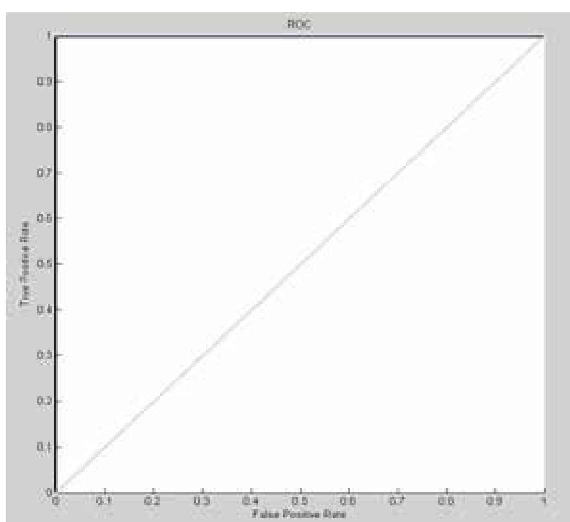

Figure 10: ROC plot of ANN Test

B. Confusion Matrix:

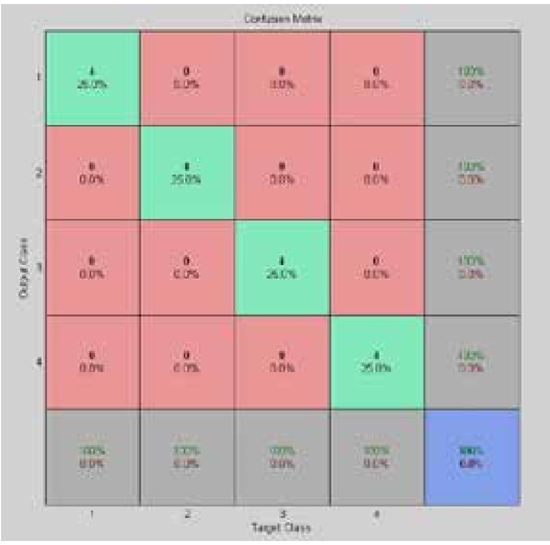

Figure 11: Confusion matrix of ANN test

The confusion matrix shown in figure 11 indicates the categorization of all 16 output class, which has been classified the way it should be. In addition to ROC Confusion matrix are easy to evaluate, as they directly indicate the no. of sample vector which were misclassified by ANN during testing. Here as shown in figure 11, it indicates that 100% classification against 4 different deviations in voltage level doesn't effects the classification. Hence again we can consider the robustness of ANN to identify the load with switching current signature even under voltage deviation.

CONCLUSIONS

The advance approach to identify domestic load using single current transducer has been shown. The switching current signature of the load was utilized to identify the device being turned-on. Artificial neural network was trained to recognize 4 different kind of devices using rms current signatures during switching. The test result shows that the artificial neural network, once trained with switching current signature for devices can also identify the particular load even when voltage deviation are faced which ultimately shows robustness of neural network approach in domestic load identification with only single current transducer. This method of load identification can be utilized for recognizing real-time activities of downstream loads. Hence we can drastically reduce the installation-modification, labour and cost involved in monitoring each and every device individually using artificial neural network approach.

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