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Event-based S-transform approach for nonintrusive load monitoring

***Abstract**. In this study, a nonintrusive load monitoring system is developed by analyzing the power signal obtained from a single point of power meter installation to detect ON/OFF load activities. A mathematically designed model with backpropagation neural network is utilized in load pattern recognition to decompose the load operation. Leveraging its unique load signature profile, the S-transform approach is employed to extract the features from the aggregate power signal and analyze the detection of load start-up transient from signal processing. To improve the accuracy of load identification for unknown data, the power factor is used as an additive feature with 99.32% load recognition accuracy.*

Streszczenie.** W artykule analizowany jest system monitorowania obciążenia sieci. Wykorzystano sieć neuronową do rozpoznawania rodzaju Transformata S jest użyta do ekstrakcji danych z sygnału mocy. Dodatkowo do identyfikacji obciążenia użyto współczynnik mocy. **Metoda monitorowania obciążenia systemu energetycznego wykorzystująca transformatę S.

Keywords: load recognition, feature extraction, artificial neural network, S-transform
Słowa kluczowe: rozpoznawania obciążenia, sieć neuronowa, transformata S

Introduction

The power system has become a complex network with the emergence of distributed generation. Smart grids provide a new set of technology-based tools by integrating both load and generator sections to allow a grid to be fully optimized [1]. The smart meter is one of the components in a smart grid system; it can be used to monitor the load performance by conducting a detailed analysis of the energy demand signal from the consumer site.

By monitoring the load activity, users are provided with valuable information, which facilitates the identification of inefficient appliances, inefficient energy usage, and load shifting according to the time of day when energy is cheap. In the low-voltage level, load is monitored by measuring the energy demand, which is caused by individual and composite load operations in the building, through the use of two methods, namely, intrusive and nonintrusive.

In the past, load is monitored by installing the power meter in every appliance of interest; this method is called intrusive load monitoring. This method can monitor the load in real-time and accurately reveals energy usage. However, the high cost and implementation of abundant power meters could affect system reliability [2]. Hence, a solution known as nonintrusive load monitoring (NILM) was introduced to simplify the load monitoring system. Hart [3], a pioneer of the NILM system, proposed a method to disaggregate the load activity from the total measurement at the panel meter level based on a steady state detailed analysis. Nonintrusive method requires low-cost power meter installation and is easy to implement in the consumer sector.

Previous work indicates that current and voltage signals are extracted through steady state [4], transient, or a combination of both analyses [5, 6]. Steady state analysis considers the change state from one energy level to another new energy level with specific thresholds. Transient analysis takes advantage of the drastic start-up current of a unique load profile, which can be stored as a database to implement load detection from the total energy demand. To improve load decomposition, a combination of both analysis methods is employed to provide more information in the form of different signals to identify the load. The authors in [7] showed the advantage of the power factor feature approach in detecting appliance operation. An advance feature extraction transform was manipulated to discriminate the load signature by using wavelet transform [6] to overcome the limitation of Fourier transform, which does not properly locate the time when the event occurred [8]. However, wavelet transform does not provide the frequency invariant amplitude response [9]. Pattern recognition has been explored as a method to classify the target appliance in the NILM context. Supervised machine learnings, such as artificial neural network (ANN) [10, 11], support vector machine (SVM) [8], and fuzzy logic [12], were utilized in the past to identify the load. Particle swarm optimization (PSO) and genetic algorithm (GA) are considered improvements of previous methods [13].

In this study, an event-based method for load identification is employed by leveraging S-transform feature extraction to provide a different signal of the load profile for non-periodic electrical signals based on the time–frequency representation of a time series signal [14]. Edge detection is analyzed by image processing for transient load switching based on the appliance energy level. A backpropagation neural network (BP-NN) is selected as the pattern recognition tool for NILM modeling because it is commonly used in load decomposition. The proposed feature extraction is appropriate for steady state analysis as the event and disturbance in the signal can be detected with respect to time. To prove the robustness of the developed model, unknown data are tested to evaluate system performance. The power factor is considered an additive feature in this work to increase the load identification accuracy for unknown data tests.

S-Transform to detect the event in a non-periodic signal

S-transform (ST) is a signal processing technique that produces a time–frequency representation of a time series signal. Compared with wavelet transform (WT), ST represents a progressive resolution that retains absolutely referenced phase information and has a frequency-invariant amplitude response. ST is a revolution of the continuous wavelet transform (CWT), which is based on a moving and scalable localizing Gaussian window. The ST function, $x(t)$, can be derived as a CWT function multiplied by a phase correction factor, $e^{-i2\pi f\tau}$ [15]. To derive ST, CWT needs to be considered as a series of correlations of the time series with a wavelet-like function in Equation (1).

$$(1)\qquad W(\tau,d)=\int_{0}^{\infty} x(t)\omega(t-\tau,d)dt\ ,$$

where $\omega\ (t-\tau,d\ )$ is the mother wavelet, t and τ both denote time, and dilation factor d is the inverse of frequency f.

The mother wavelet can be expressed as Equation (2).

$$\omega(t,f)=\frac{|f|}{\sqrt{2\pi}}e^{-\frac{t^2f^2}{2}}e^{-i2\pi ft}dt \qquad (2)$$

According to Equation (2), the mother wavelet does not fulfill the condition of having a zero mean, and it is not strictly a CWT [16]. Therefore, ST is obtained by multiplying CWT, $W(\tau,d)$, with a phase factor. By substituting Equation (2) into Equation (1), the ST equation is

$$S(\tau,f)=\frac{|f|}{\sqrt{2\pi}}\int_{-\infty}^{\infty}x(t)e^{-\frac{t^2f^2}{2}}e^{-i2\pi ft}dt\,. \qquad (3)$$

Combining frequency dependent resolution with absolutely reference phase allows the time average of ST to be equal to the Fourier spectrum. Therefore, ST simultaneously estimates the local amplitude spectrum and the local phase spectrum. The output of ST is a 2D matrix where rows pertain to frequency and the columns represent time. Each element in the matrix is a complex number. The information in the ST matrix can be plotted as time–frequency contours, which facilitate the analysis of signal changing detection via visual inspection of the energy level.

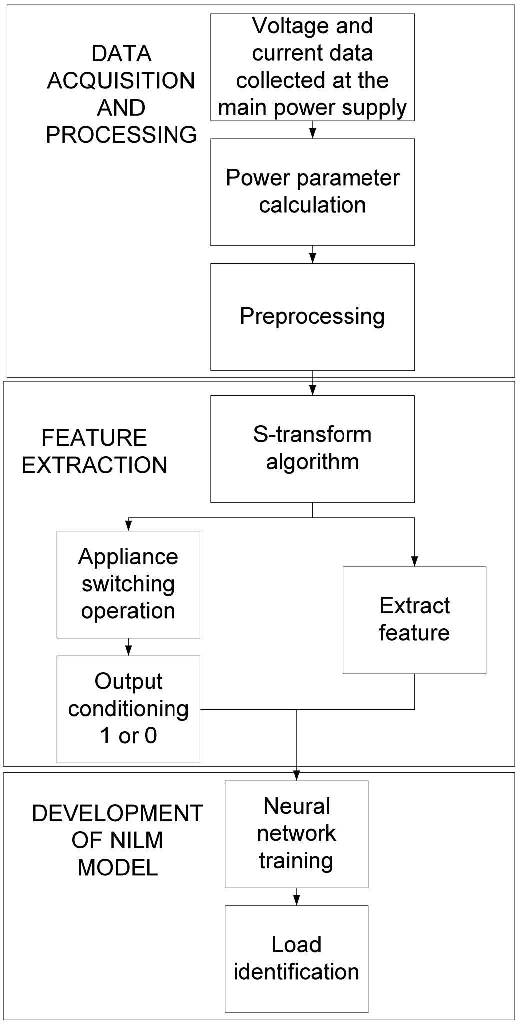

Fig. 1. Block diagram of the proposed NILM system

Proposed NILM method

An NILM system was developed in this study by leveraging ST feature extraction of the real power of the total measurement for edge detection and by creating a new dimension of the load signature signal based on time–frequency to monitor a circuit of fluorescent light with 14 tubes, an airconditioner, and a computer. The power meter is capable of measuring real power (*P*), reactive power (*Q*), the power factor (*PF*), apparent power (*S*), and Irms and Vrms parameters. The power factor is considered as an additive feature because of its good contribution to load decomposition when simulated with unknown data. A block diagram of the proposed method is shown in Figure 1.

Data acquisition

The power meter was installed at the main entrance of the power source. Experiments were conducted under real scenario with 50 Hz supply from the power distribution. The sampling rate used for data acquisition was 1 Hz. The capability of the meter allows signal processing based on start-up transient and steady states of the load signature. Supervised learning data acquisition, which carries out load switching manually and systematically by covering all combinations of possible events, was considered to illustrate the energy demand pattern of the monitored appliances.

Preprocessing of data

In this stage, raw data need to undergo a filtering process by employing a median filter to remove the noise in the signal. Median filtering is used to produce big edge jumps between different transition states, thus smoothing and reducing the noise of the raw signal without removing important information, such as the transient of the appliance that stands for the last few seconds. The raw data collected in this experiment are fined tuned by removing the noise in the signal with a median filter, which simply selects the median value of the sequence to represent the current value [5].

Feature extraction

Feature extraction is a form of signal processing to transform a pattern from the actual form into a new form without eliminating the event occurring in the signal. The collected energy demand could show the possibility of appliance activity based on appliance switching. The real power data collected from the main incoming power supply are used to compute ST to form a map of complex numbers in the ST domain. The ST matrix with N columns and $M = (N/2) + 1$ rows is obtained after employing ST according to the signal. The feature that represents the event in the real power signal is extracted from the ST analysis in terms of time–magnitude. The ST of the real power signal can be obtained with Equation (4).

$$Ws_{i,j}=\frac{|f|}{\sqrt{2\pi}}\int_{-\infty}^{\infty}W(t)e^{-\frac{t^2f^2}{2}}e^{-i2\pi ft}dt\,, \qquad (4)$$

where $Ws_{i,j}$ is the S-matrix for real power (W), i is the number of columns related to time, and j is the number of rows related to frequency.

Further ST analysis was performed by computing the difference between time–frequency values to obtain a shift in the signal by the inverse of the original signal to produce a high dimension in the signal. The difference in the time–frequency equation is provided by Equation (5).

$$\Delta Ws_{i,j}=\left|Ws_{i,j}-(Ws_{i,j}-1)\right|, \qquad (5)$$

where $Ws_{i,j}$ is the current S-matrix value and $Ws_{i,j}-1$ is the previous S-matrix value.

The correlation between the standard deviation and event occurring in the signal is shown in Figure 2. The proposed model seeks to use a combination of power parameters as inputs for neural network training in an effort to assess the optimum load identification model. Then, the

ST based on time–magnitude is analyzed by selecting standard mathematical statistical indices, such as maximum, minimum, mean, standard deviation, and kurtosis. A detailed analysis is evaluated by testing the effectiveness of the extracted feature according to neural network modeling.

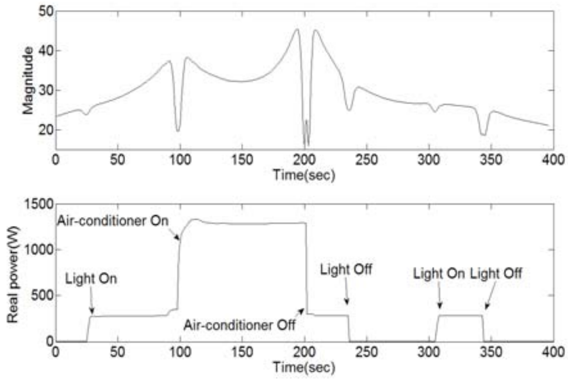

Fig. 2. ST standard deviation plotted with respect to the real power event

Therefore, standard deviation is considered a pool feature in neural network training because of its effectiveness in load decomposition. Standard deviation analysis can be utilized to characterize the event occurring in the signal in terms of time–magnitude representation. ST feature analysis can be derived as Equation (6).

$$F_{ST} = std\left(\left|\Delta Ws_{i,j}\right|\right), \tag{6}$$

where F_{ST} is the vector value of the standard deviation for all columns in the delta ST matrix.

Detection of appliance switching operation

Based on the signal analysis, a visual inspection based on the ST approach was performed to detect the load operation event from the switching activity. By plotting the ST matrix, the decomposition of load type and activity can be detected through the analysis of the energy level. Owing to the drastic difference in the power consumptions of the fluorescent light, airconditioner, and computer, the complex value in the ST matrix needs to be normalized with $log(1 + x)$ so that the image will represent a satisfactory event. Figure 3 shows the edge detection analysis process for load switching. The condition for output training neural network can be labeled based on appliance operation switching. Only two states of appliance operations are considered, namely, 0 and 1 referring to the ON and OFF appliance operations, respectively.

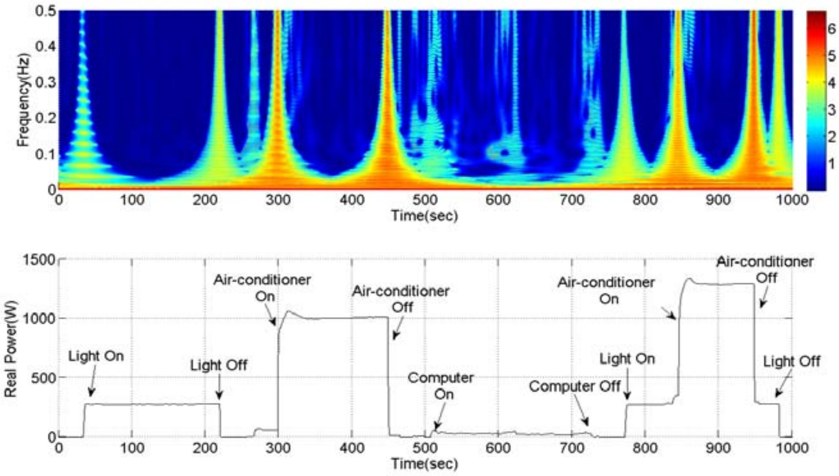

Fig. 3. Edge detection based on load switching

Application of Neural Network for Automatic Load Identification

Multi-layer perceptron feed-forward with BP-NN is selected as the pattern recognition tool because it is among the most applied classification algorithms in load decomposition. Training was performed with "logsig" as the transfer function and "trainlm" as the training function because of the fast and good training in neural networks. The advantage of implementing the neural network method is that the performance of the network model can be increased by adjusting the hidden layer structure to obtain the best model. After data preprocessing, the pool feature was arranged systematically as the input for the neural network training. The structure of a multilayer feed-forward network is shown in Figure 4. The input features with normalized data are the active and reactive powers (P, Q), power factor (PF) and ST feature (F_{ST}) and the corresponding three outputs are the operation states of the appliances, namely, fluorescent light, air-conditioner and computer. To determine the appropriate hidden layer neuron, the BP-NN was programmed with the initial training algorithm with the objective of computing the lowest mean square error for the best hidden neuron evaluation followed by the best model design.

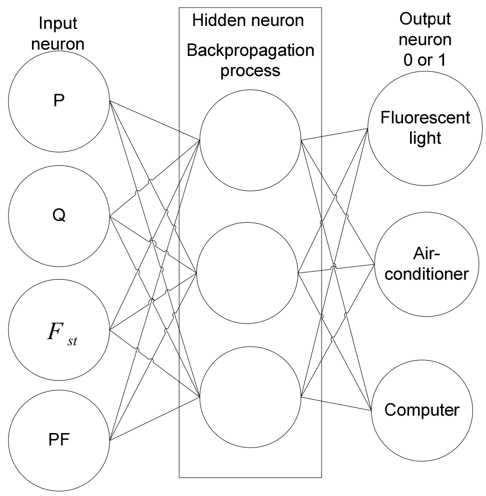

Fig. 4. Example of the MLP-BPNN structure

Neural network training

The number of samples used for training was 2664 datasets. The number of possible appliance switching combinations in this experiment was 8 combinations ($2^3 = 8$). The datasets were divided into three blocks of datasets, namely, 60% of training data, 20% of validation data, and 20% of testing data. The objective of implementing dataset division is to avoid over fitting during training and to ensure the efficiency of the developed model. The number of training data for the ON and OFF states after the division process is listed in Table1. The input data are normalized so that the value fall between 0.1 and 0.9 to enhance the network performance [17]. Normalization was perfomed in this study with Equation 7.

$$\bar{x} = \left(\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}} \right) \times 0.8 \right) + 0.1 , \quad (7)$$

where $\bar{x}$ is the normalization variable, x is the variable to be normalized, x_{min} is the minimum value of the variable, and x_{max} is the maximum value of the variable.

Table 1. Number of training data according to the ON and OFF states

Appliances	Number of OFF state training data	Number of ON state training data
Fluorescent light	278	255
Airconditioner	361	172
Computer	325	208
Total	964	635

Neural network for unknown data performance

An unknown dataset was utilized in the next simulation to test the robustness of the developed model under a real scenario of variation in the power system. A total of 2954 datasets were used to test the BP-NN model. The number of testing data representing the on and off states of the appliances is listed in Table 2. The input data are normalized so that the value fall betweeThe data are numbers for the testing data are tabulated in Table 2.

Table 2. Number of unknown data according to the ON and OFF states

Appliances	Number of OFF state testing data	Number of ON state testing data
Fluorescent light	302	143
Airconditioner	293	152
Computer	339	106
Total	934	401

Test Results

This section describes the results obtained from the proposed method to identify the ON and OFF states of appliances. Given that the output obtained after the simulation is not as expected, output processing needs to be performed after the simulation. Therefore, the estimated result obtained can be analyzed by comparing it with the output target of the dataset.

Table 3 shows the testing results for the BP-NN model considering several input features. From the results, it is noted that the accuracy of the model and correct classification of the appliances can be increased by considering the appropriate features in the training of the neural network. The performance of the developed BP-NN is assessed based on the correct classification and misclassification of data, with accuracy recognition as a benchmark of the NILM system.

The number of time slices in which an appliance is correctly classified as being ON is referred to as true positive (TP), classified as being ON when it is actually OFF is referred to as false positive (FP), classified as being OFF when it is actually ON is false negative (FN), and correctly classified as being OFF is true negative (TN). All obtained classification results show high prediction accuracy (above 90%).

Effective input features need to be considered to decrease misclassification of prediction data, thus increasing the accuracy of load operation recognition. In this case, the ST feature and power factor are considered as effective input features that can give better BP-NN prediction accuracy. The results for validating the BP-NN with unknown data are tabulated in Table 4. The results showed the power factor is considered as an effective input feature because it gives the best prediction accuracy with the least misclassification. Based on the results shown in Tables 3 and 4, misclassification of unknown data is high compared to the testing data.

Table 3. Results of the BP-NN model with testing data

Input feature	Correct classification	Misclassification	Accuracy recognition (%)
P	522	11	98.06
$P\ Q$	527	6	98.94
$P\ Q\ F_{ST}$	532	1	99.81
$P\ Q\ F_{ST}\ PF$	532	1	99.81

Table 4. Results of the BP-NN model with unknown data

Input feature	Correct classification	Misclassification	Accuracy recognition (%)
P	545	46	92.22
$P\ Q$	549	42	92.95
$P\ Q\ F_{ST}$	565	26	95.54
$P\ Q\ F_{ST}\ PF$	587	4	99.32

Conclusion

An NILM method was developed to identify the operation states of electrical appliances by using a multi-layer perceptron BP-NN with combined power parameters, power factor and ST feature as input features. The pattern obtained for each appliance is considered unique as a human fingerprint that can be detected from the total energy demand. Based on the pool feature patterns, a BP-NN has been developed to classify the three types of electrical appliances (fluorescent light, air conditioner and personal computer) according to their operation ON and OFF states. To assess the robustness of the proposed BP-NN, it was tested with unknown data. Test results showed that the proposed BP-NN model achieved 99.32% classification accuracy by using the combined P, Q, F_{ST}, and PF features when tested with unknown data. The computer showed the highest misclassification compared with the fluorescent light and air-conditioner. This result is due to the condition that the power consumption of the computer is too low compared with that of the fluorescent light and the air-conditioner. In addition, the continuous variation in the computer signal made predicting its operation state difficult.

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