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Group control and identification of residential appliances using a nonintrusive method

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Abstract: Identifying and controlling (ON/OFF) electrical appliance(s) from a remote location is an essential part of energy management. This motivated us to design a system that can collect the aggregate load signature from a single point, obtain the features, and finally identify the ON state of electrical appliance(s). The proposed disaggregation technique can be divided into two modules: the first part proposes an electrical installation system to disaggregate the appliance at the circuit level, whereas the second part consists of feature selection, dimension reduction, and classification algorithms. Load signatures of electrical appliances were combined with white Gaussian noise to analyze how noise affects the classification results. Amplitudes of the major eight harmonics of load signatures were selected as a feature for the classification. Various classification algorithms were applied to data to check their feasibility. The comparative evaluation showed that among the considered classifiers, the multilayer perceptron-artificial neural network (MLP-ANN) classifier leads in classification accuracy with 99.18%. If the system is combined with noise, the accuracy decreases to 93.10%. This paper also shows that the proposed technique reduces the space complexity and decision time of the smart meter.

Key words: Smart meter, load signature, harmonic amplitude, artificial neural network, support vector machine, Bayes classifier

1. Introduction

In most developing countries, the limited sources of power generation are not able to fulfill the electricity demand, which raises the gap between demand and supply. This gap can be reduced mainly with the help of three means: i) Curtailment of load (outage); this method leads to revenue loses or consumer dissatisfaction. ii) Increase in the power generation; beneficial, but a long-term process that requires a lot of investment. iii) Load management; a better solution for the present scenario. A smart meter can be efficiently used for load management, which includes features like appliance identification, control, and fault analysis of household appliances. Additionally, smart meters allow for billing transparency and dynamic pricing technology. Generation of more power than is actually needed from conventional sources is accompanied by CO_2 emissions. Thus, it is essential to incorporate renewable sources into the conventional systems. In this context, the role of the smart grid system has assumed greater importance. The nonconventional energy sources used at domestic levels can be incorporated in a distributed network with the help of smart meters. This is where a smart meter is different from the electronic version of the energy meter. Smart meters help meet the electricity demands of consumers during peak load periods, or supplement the increase in demand by incorporating the renewable energy and storage system. A full-length discussion on the merits of the use of smart meters in smart grids and microgrids can be found

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in [1,2]. In a smart meter system, device identification is an important application for recognizing different household appliances. In the case of various appliances connected together, this feature allows users to monitor load profile and power consumption separately. Hence, smart meters ought to be installed in every household. There are two means to carry out device identification: i) the intrusive method and ii) the nonintrusive method. In the first method, each appliance is connected through a dedicated sensor, known as a plug meter, which detects the load profile and power consumption of the connected load. This technique is reliable in terms of accuracy; however, the association of each appliance with a sensor makes it expensive. It also demands changes in household electric wiring. The second method, nonintrusive load profile monitoring, consists of the following steps: i) acquisition of load signature, ii) extraction of features and events, and iii) classification of features and events. Despite its complex signal processing, this method is economical in nature and works with existing household electrical wiring systems. One of the earliest approaches to nonintrusive load monitoring, developed in 1980 at MIT by Schweppe and Hart, has its origin in load monitoring for residential buildings [3].

As shown in Table 1, multiple features were chosen and/or low classification accuracies were obtained. Recently, Wang and Zheng [10] proposed a method for residential appliance identification, where they categorized the appliances according to working style. Appliances were then classified by choosing multiple features. Even after applying principal component analysis (PCA), a large number of features increased the time and space complexity of the system. Spectral components were used as the feature in [6], where authors performed simulations rather than real-time experiments and obtained results in ideal conditions. Further noise was added to mimic the original; an average accuracy of 92% was obtained. Table 1 summarizes the recent related research work, methodologies, and their limitations and remarks. This paper proposes a simple method for appliance disaggregation where a single-feature, multiple-algorithm approach gives the solution with the best-known accuracy. The authors worked on a real-time system, which was developed in the laboratory, to acquire the current signature of various appliances and extract the features from it. Figure 1 demonstrates the framework of the experiment.

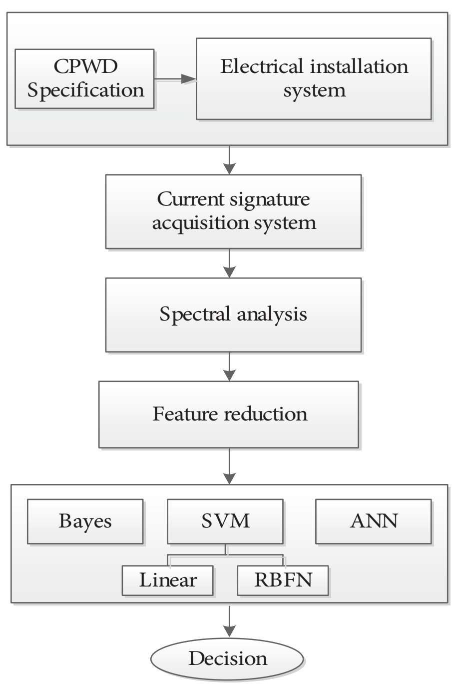

Figure 1. Framework of the experiment.

Table 1. Related works in the area of load segregation.

No.	Load segregation technique	Features	Year	Limitations/ remarks
1	Artificial neural network approach for harmonic source detection.	Spectral components (real and imaginary).	2006	Complex and time-consuming, claimed average accuracy was 92% [4].
2	Pattern recognition algorithms, committee decision mechanism.	Active power (P), reactive power (Q), power factor (PF), admittance waveform ratio, power waveform, eigenvalues of waveform, and transient waveform power over half cycle.	2010	Huge number of features increased the complexity of system [5,6].
3	Wavelet analysis used for feature extraction.	Wavelet transform instead of FFT for feature calculation, wavelet features of several consumers' electronics appliances.	2010	Accuracy was not claimed [7].
4	Event detection and classification.	Steady-state current, switching transient current, and working style of appliance.	2011	Accuracy was not claimed [8].
5	Home electrical signal disaggregation using ANN and wavelet technique.	P, Q, PF, changes in real power along with appliance-specific decision rules and pattern recognition approach.	2012	Complex decision rules and pattern recognition approach; accuracy was around 95% [9].
6	Residential appliances' identification and monitoring by a nonintrusive method.	Event detection, STC, P, Q clustering technique was applied.	2012	Accuracy around 80%, claim of effectiveness of method in presence of noise but analysis was not done [10].
7	Observations of features over several days, identification on NIAFE.	Steady-state and switching transient current working styles identification and feasibility analysis.	2013	Needs several days for observations. Controlling of appliances was not discussed, accuracy was less than 70% [11].
8	Simplified procedure for appliance identification.	P, Q, PF, harmonics, harmonic amplitude.	2013	More features leads to a slow system, no accuracy was claimed [12].
9	Independent component analysis (ICA) for home appliance separation.	ICA was used to separate the current signature of individual appliances for the composite load.	2013	Useful for two appliances' disaggregation, accuracy was around 80% [13].

2. Methodology

2.1. System overview

Figure 2 demonstrates the electrical installation overview, which is designed according to the Central Public Works Department of India (CPWD). The CPWD's specifications for internal electrical installation are:

(i) Low-power circuits shall feed appliances like lights, fans, call bells, mobile chargers, etc. Each circuit in the home will be connected with either 800-W load capacity or not more than 10 utility points. However, in case of fewer power appliance points, where load per point may be less, the number of points may suitably increase.

(ii) Each high-power circuit in residential buildings can feed the following outlets:

a) Not more than two 16-A outlets.

b) Not more than three 6-A outlets.

c) Not more than one 16-A and two 6-A outlets.

(iii) Loads greater than 1 KW shall be controlled by suitably rated miniature circuit breakers and cable size shall be decided as per the calculations.

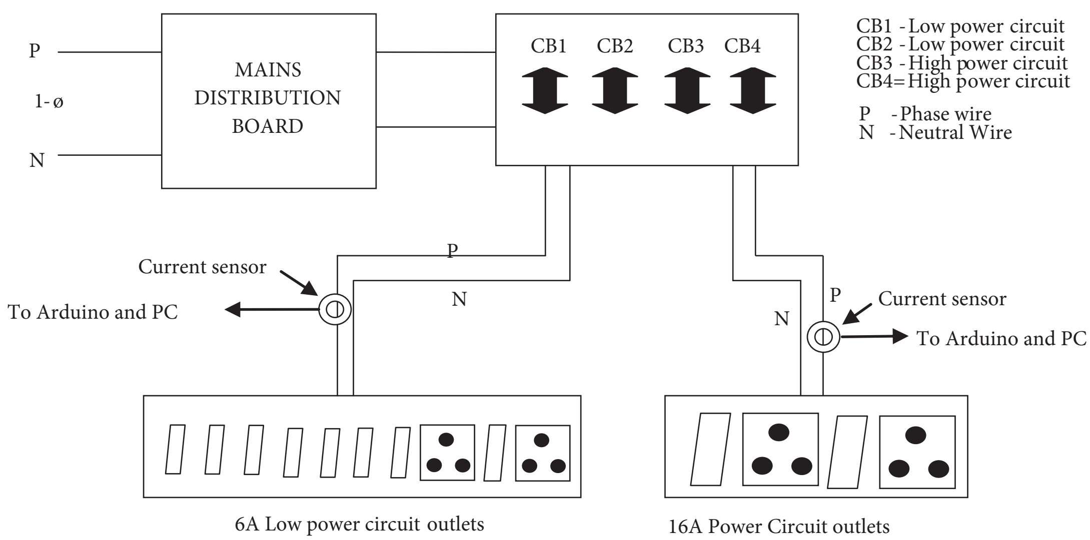

Figure 2. Diagram of the electrical installation according to CPWD specifications for domestic utility.

These specifications provide a primary desegregation between low- and high-power consumption appliances and limit the number of appliances on one circuit board. Figure 2 shows a schematic of an electric installation system where the main distribution board receives a single-phase power supply that is evenly distributed among various circuit boards. One circuit board consists of four circuit breakers (CBs) to control the four different switch boards. CB1 and CB2 control low-power outlets (switch board) and CB3 and CB4 control power circuit outlets. Current sensors are coupled with the phase wire departing toward the switch boards (lighting and power outlets) and the output of the current sensors connected to the analog port of an Arduino Mega 2560 development board, as seen in Figure 3.

3. Implementation

Figure 3 shows an overall schematic of the home appliance identification system designed and developed in the laboratory. A current sensor (SCT-013-030) was installed on the phase line, which acquires the load signature of an individual or composite load. This current sensor is a current transformer based on the Hall effect and converts the heavy mains line current into low voltage. This voltage worked as the input signal for the

Arduino Mega 2560 board. This board is basically a data acquisition card that provides an interface between a personal computer and a current sensor. A PC with MATLAB Version is 7.14.0.739 (R2012a), updated with the MATLAB-Arduino interface package, received signals from the Arduino Mega 2560 board. All signals are acquired on the Arduino card and further processed on the MATLAB platform. The signal was acquired with a sampling rate of 20,000 samples/s. Features (i.e. harmonic amplitude) were obtained online by applying a fast Fourier transformation (FFT) algorithm on the acquired load signature; these features were used for further classification processes. In addition to the disaggregation of home appliances, developing logic to control the appliance using relays was our further research motivation. The experiment was performed for eight household appliances. The total possible combinations of load signature of eight appliances was 256.

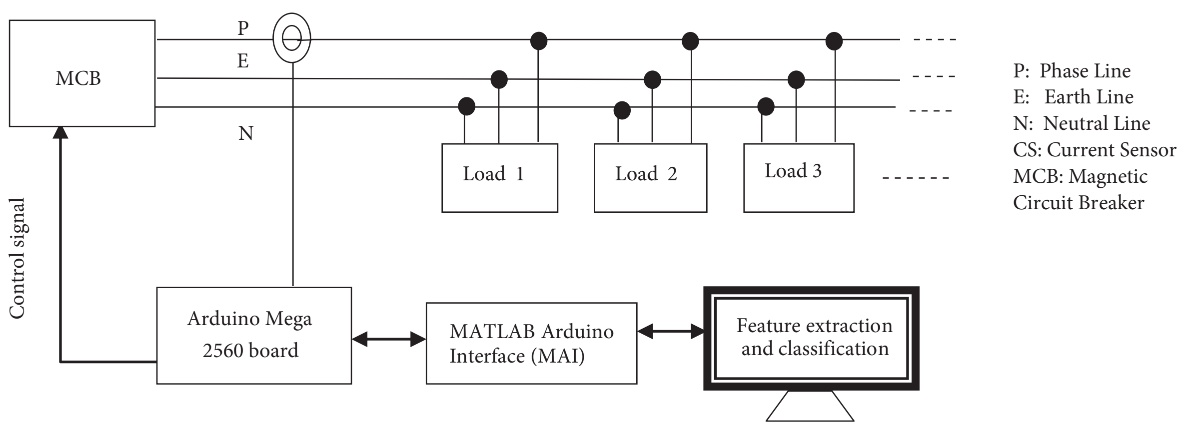

Figure 3. Overview of the system.

If 256 combinations were used, the representation of the result would be difficult to understand well; the data samples would be too huge to train the network. To analyze only feasibility at the experimental level we randomly chose 60 classes out of a total of 256 and equally divided them into 5 different sets. The random sampling method avoided set fixed patterns that might otherwise be a possibility. The classification accuracies obtained for each combination of the five sets are presented.

3.1. Feature extraction

Figure 4 shows the current signature and respective spectral plots for some of the selected appliances. The analysis of the waveform is nearly impossible, whereas analysis of the spectrum is easy and its property can be used as the features because the current signature of each appliance or any combination of appliances has its unique Fourier transform. Harmonics amplitudes of load signatures are the potential feature for disaggregation of home appliances [14]. First, 8 odd harmonics were selected as the features. Low amplitudes of higher harmonics contain insignificant information at the cost of a large data set. Table 2 shows the list of appliances and their specifications that were used in the experimentation.

The dimensions of the feature matrix were further reduced using PCA. PCA is a dimension reduction method that uses orthogonal transformation to convert a set of features of possibly correlated variables into a set of values of linearly uncorrelated variables. These linearly uncorrelated variables are known as principal components (PCs). Maximum variation in the input information mapped by the first principal component (PC1) and other principal components (PC2, PC3, and so on) are in descending order of variation without losing too much input information. We restricted our input data to only two principal components, PC1 and PC2. The reduced input vectors were fed to the various classifiers.

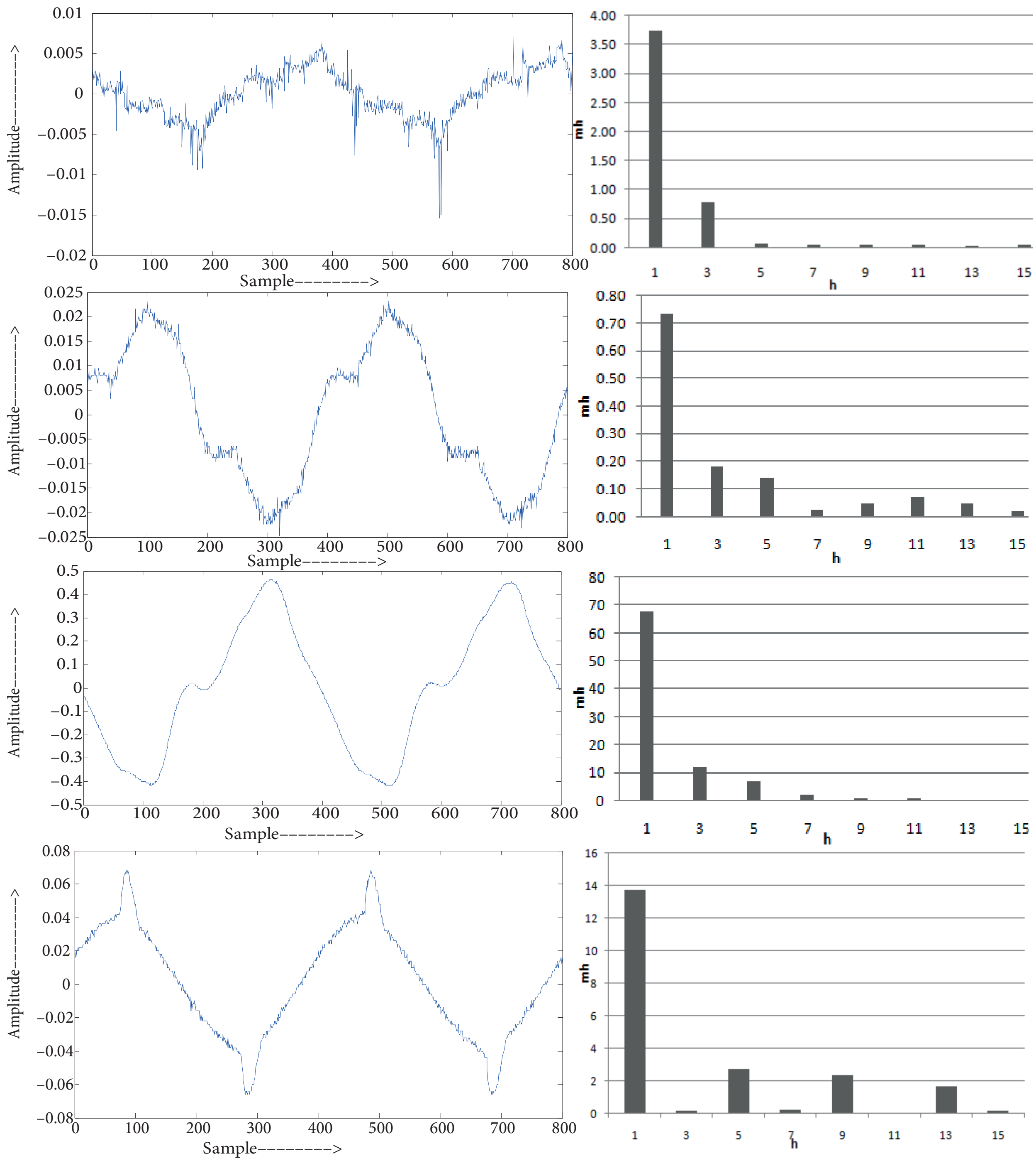

Figure 4. Current signature and spectral components of a) CFL, b) AC, c) TV, and d) combination of incandescent lamp, tube light, CFL, and laptop.

Table 2. Appliance names and their specifications.

No.	1	2	3	4	5	6	7	8
Appliance name	Incandescent lamp	Tube light	CFL	Laptop	TV	Fan	Induction stove	Monitor
Specifications	60 W, 230 V lamp	40 W, 230 V	15 W, 240 V, 50 Hz,	19.3 V 3.1 A	168–240 V, 0.4 A, 85 W	50 W	Variable wattage level 600–1400 W	19 W, 47 cm

4. Data classification

The aim of this study was to identify the most appropriate classifier to predict the state of appliances, i.e. ON/OFF. The data sets were analyzed using classifiers based on supervised learning, namely Bayes, support vector machines (SVMs), and the multilayer perceptron-artificial neural network (MLP-ANN). Initially, the data were randomly divided into two sets: training and testing sets. Training sets are used as input data to train the classifier network. After training is completed, classifiers are able to discriminate the test data in to various target classes.

4.1. Noise analysis of current signatures

Noise levels were checked to evaluate the classifier performance; the acquired electric signals generally contained white Gaussian noise [15]. The classifier was tested with added white noise signal (50 dB S/N ratio) to simulate a real-time environment. Figure 5 shows the effect of noise on the spectral amplitude of current signature. It was observed that if noise was present in the signal, then some additional harmonics were present in spectral analysis. It was also seen that as the noise level increased (that is, as the S/N ratio decreased), there was fluctuation in the amplitude of harmonics. In the feature space, the feature vector was inseparable due to added noise as shown in Figure 6, which led to poor classification accuracy.

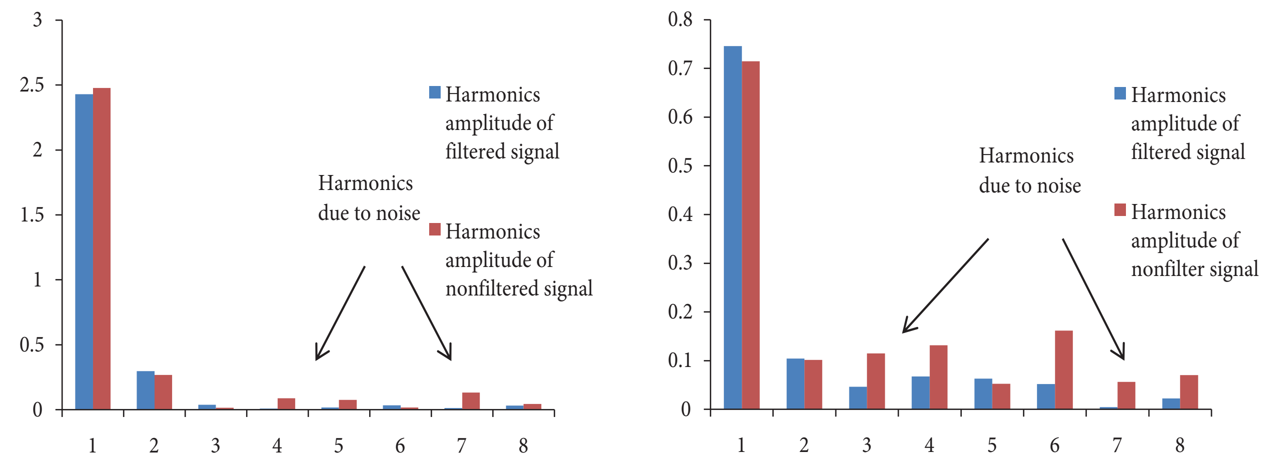

Figure 5. Effect of noise on the harmonic component of the signal.

4.2. Bayes classifier

A Bayes classifier is optimal in minimizing the probability of misclassification. For a given "zero–one" loss function, it minimizes the risk of misclassification. However, it requires full knowledge of the underlying class conditional density for classification. In practice, the class conditional density is never known; however, a good estimate can be extracted from training data using maximum likelihood, expectation maximization, and other standard nonparametric methods. For the general case with risks, the discriminate function is $g_i(x) = -R(\alpha_i \,|\, x)$, since the maximum discriminate function will then correspond to the minimum conditional risk. For the minimum error rate case, we can simplify things further by taking $g_i(x) = P(\omega_i \,|\, x)$, so that the maximum discriminate function corresponds to the maximum posterior probability. Clearly, the choice of discriminate functions is not unique. More generally, if we replace every $g_i(x)$ with $f(g_i(x))$, where $f(\bullet)$ is a monotonically increasing function, the resulting classification is unchanged. This observation can lead to significant analytical and computational simplifications.

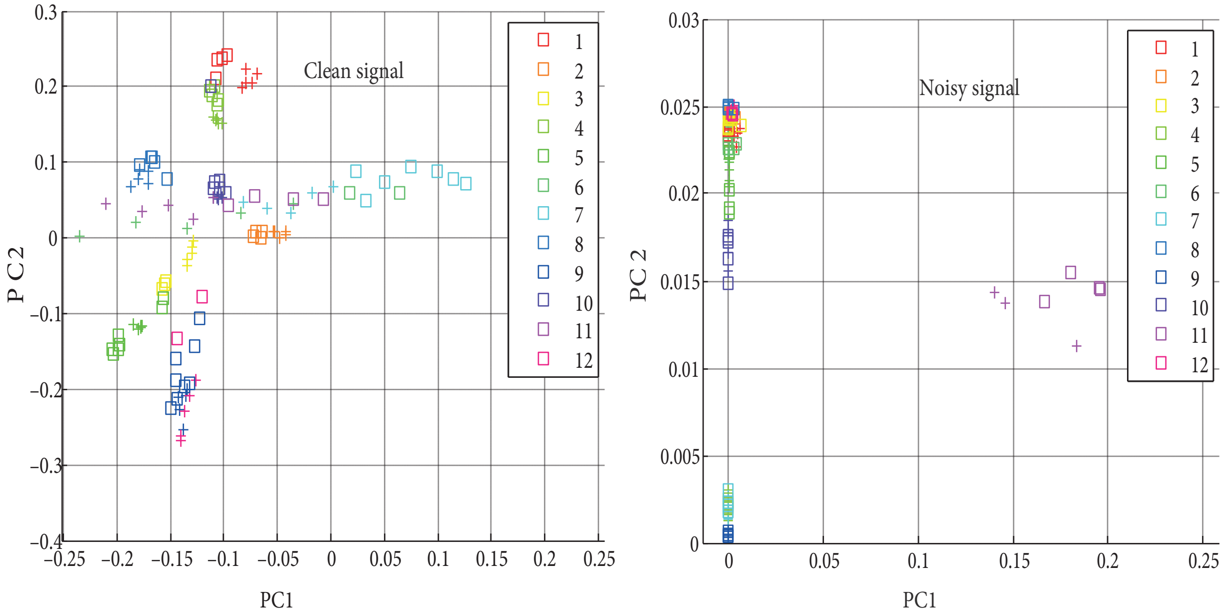

Figure 6. Feature space comparison of noisy and filtered signals in the naïve Bayes classifier.

4.3. Support vector machine

Recently, a new tool from the artificial intelligence field called SVM [16] has gained popularity in the machine learning community. The SVM classifies data by finding a hyperplane that can easily separate one class of data points from another. Thus, it aims at finding the best hyperplane with maximum marginal distance between two classes. The simplest way to divide two groups is with a straight line, flat plane, or an N-dimensional hyperplane. If the points are separated by a nonlinear region, a nonlinear dividing line is necessary. Rather than fitting nonlinear curves to the data, the SVM handles this by using a kernel function to map the data into a different space where a hyperplane can be used to do the separation.

4.4. MLP-ANN

The classifier network consisted of multiple layers of computational units. The working principle of the MLP-ANN is based on minimizing the error function by using a gradient backpropagation algorithm. This error function can be computed by comparing the output value and actual value. This error is feedback through the network. The weights of the network adjust in order to reduce the value of the error function. The considered network has an input layer, an output layer, and 30 hidden layers.

5. Results and discussion

Table 3 lists the performance of the different classifiers for five sets of current signatures and current signatures with added noise. The overall result in terms of accuracy was obtained by averaging the accuracy of all 5 sets. The experimental results suggested that the naïve Bayes and MLP-ANN classifiers are more favorable for load segregation than the SVM. If noise is present in the signal, it leads to inaccuracy in classification. The MLP-ANN was more adaptive to noise signal in this study. The presence of noise degraded the performance of classifiers but the results are still acceptable.

Table 3. Classification accuracy of classifier for noisy and clean signal.

No.	Sets	SVM				Bayes (%)		MLP-ANN (%)	
		Linear (%)		RBFN (%)					
		Without noise	Added noise	Without noise	Added noise	Without noise	Added noise	Without noise	Added noise
1	Set 1	77.3	66.0	82.2	74.1	98.1	84.0	98.7	90.7
2	Set 2	79.0	66.6	84.5	76.2	98.8	85.8	100.0	94.0
3	Set 3	76.1	63.0	81.3	73.3	98.1	86.1	99.2	93.2
4	Set 4	78.0	64.6	86.6	75.6	99.0	89.0	98.6	93.6
5	Set 5	75.3	67.3	80.2	71.2	96.4	87.2	99.4	94.0
Overall accuracy		77.14	65.5	82.96	74.1	98.08	86.42	99.18	93.1

Figure 7 shows the PCA plot and confusion bar plot for set 4, which has 12 classes. In the PCA plot, a plus sign shows the training sample data and a box symbol shows the tested data. The tested and training data of the same classes have overlapping clusters. The confusion bar plot facilitates better understanding of the same. In the confusion bar plot, the classes from 1 to 11 are successfully classified by the naïve Bayes classifier, whereas class 12 could not be classified accurately. The data of this class were mixed with classes 2, 3, 5, and 8. After analyzing all four classifiers, a total of 20 results were obtained for all 5 sets.

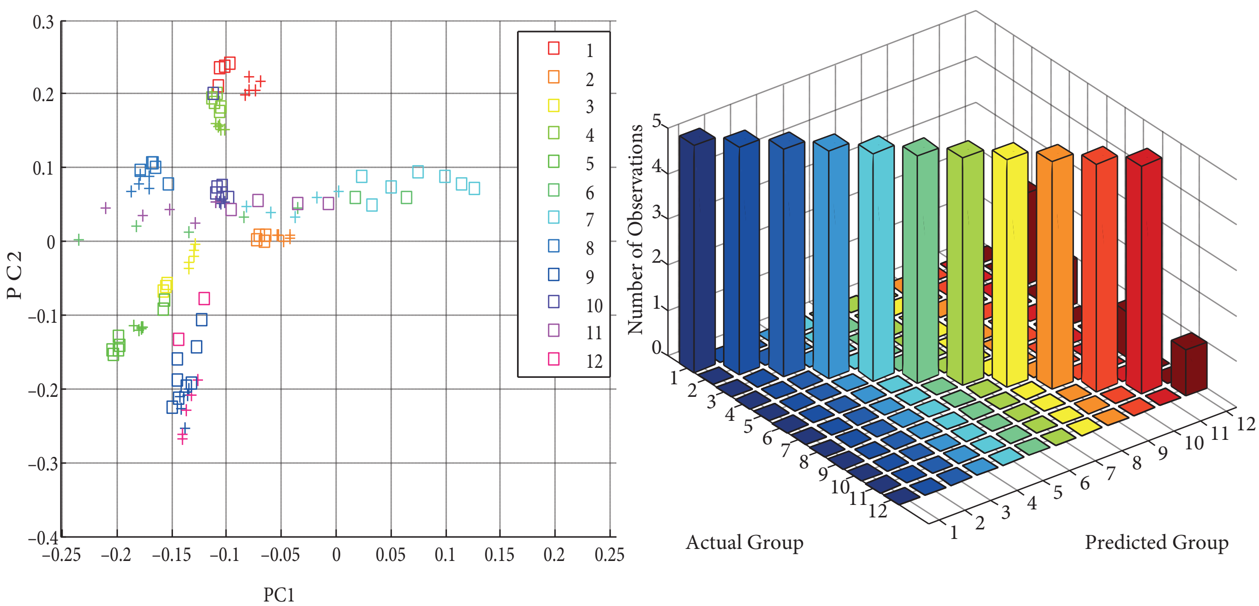

Figure 7. PCA plot and confusion bar plot for set 4 using the naïve Bayes classifier.

Figure 8 shows the PCA plot and confusion bar plot for set 4 using a SVM (radial basis function network (RBFN)) classifier. Figure 9 shows the PCA plot and confusion bar plot for set 2 using a linear SVM classifier. Figure 10 shows the confusion matrix and performance evaluation for the data in set 3. The confusion matrix shows that the optimized ANN-MLP classifier clearly classified all the classes of set 3 data except class 10, in which one element out of 10 was misclassified with class 2. The performance evaluation of the ANN-MLP classifier shows how the minimum mean square error (MSE) is decreasing for training, testing, and validation. After 13 iterations, the classifier obtained the minimum MSE.

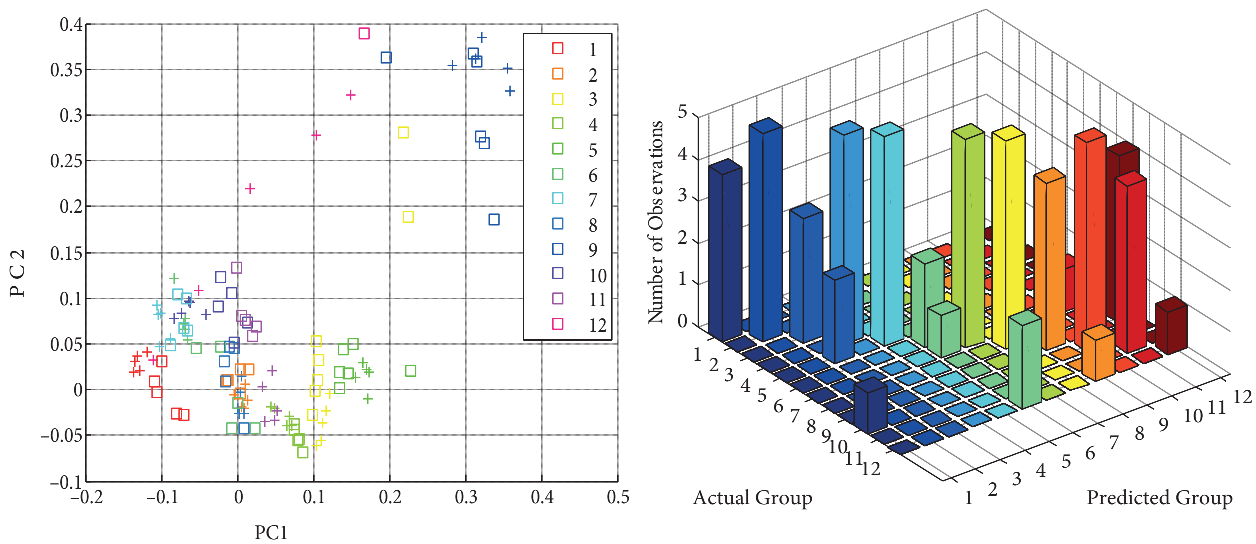

Figure 8. PCA plot and confusion matrix for set 4 using a multiclass SVM classifier in RBFN.

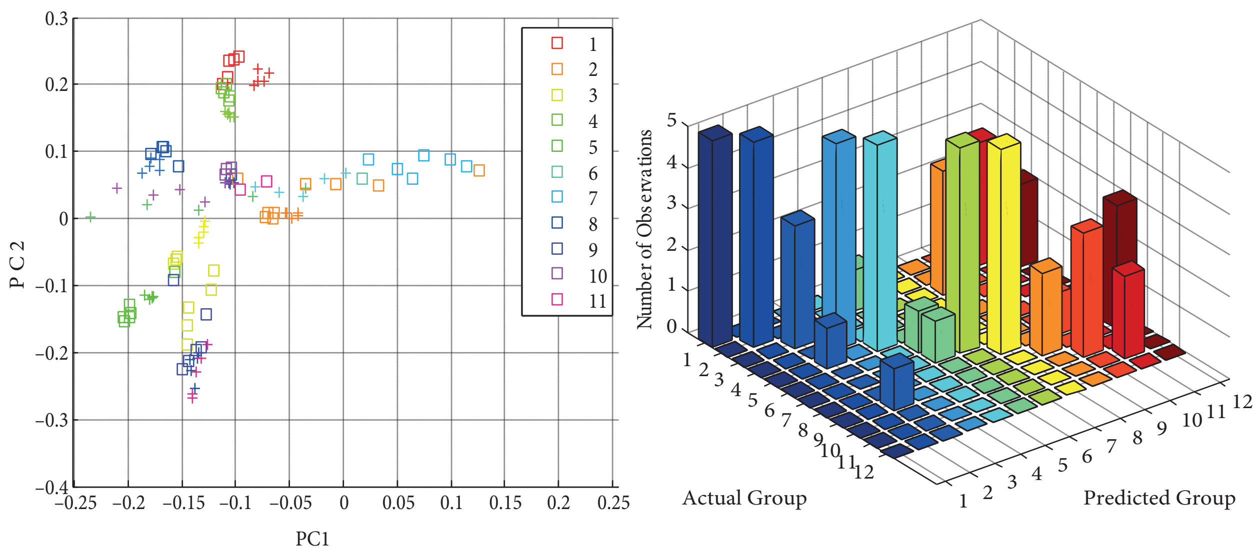

Figure 9. PCA plot and confusion matrix for set 2 using a multiclass linear SVM classifier.

The algorithm execution time was calculated for each of the five sets by acquiring the CPU timing for MATLAB Version is 7.14.0.739 (R2012a) software simulation in Windows 7 Home Premium on a PC configuration with an Intel Core i5 with 2.53 GHz processing power and 4 GB DDR3 RAM. The results shown in Table 4 prove that the single feature technique reduces execution time compared with the execution time of multifeature techniques. The difference between the execution time of a multifeature technique and a single-feature technique will increase as the number of appliances increases.

6. Conclusion

The experiment setup was designed according to CPWD specifications. Selected appliances for the experiment were installed in this circuit. Odd harmonic amplitudes of the load signature were chosen as a single feature, which was reported as a necessary and sufficient feature. This technique reduced execution time by 16.14%

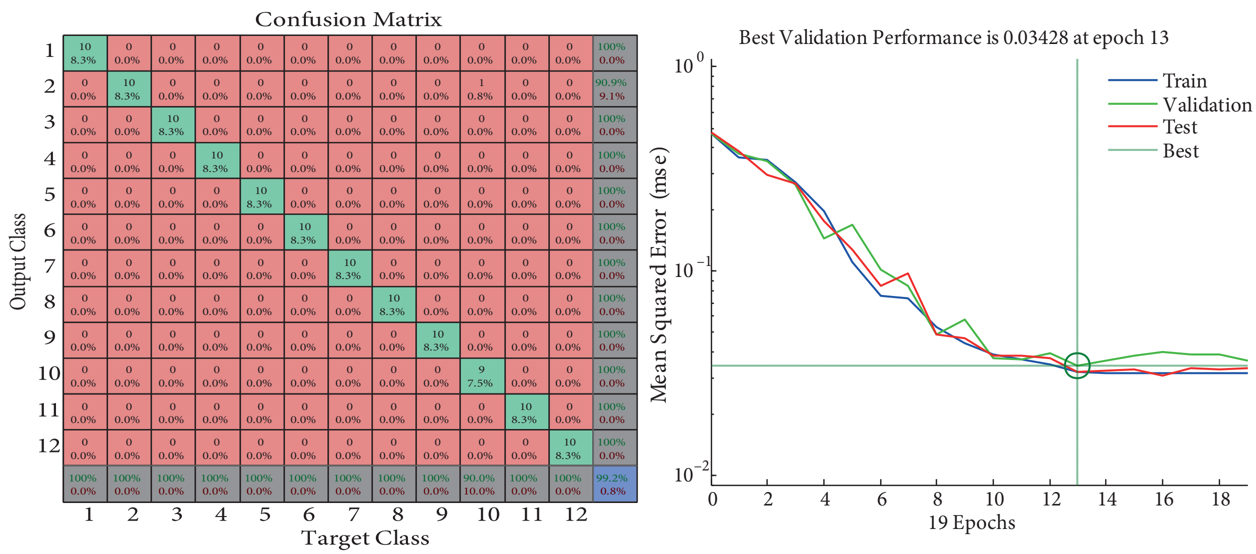

Figure 10. Confusion matrix and performance chart for set 3 using MLP-ANN.

Table 4. Algorithm execution time for multifeature and single feature techniques.

No.	Set number	Multifeature (s)	Single feature (s)	% Difference
1	Set 1	1.2792	1.2012	6.07%
2	Set 2	1.2948	1.0608	18.07%
3	Set 3	1.2798	1.0764	15.89%
4	Set 4	1.4508	1.1544	20.43%
5	Set 5	1.3884	1.1076	20.22%
Average reduction time				16.14%

compared to the multifeature techniques. SVM, Bayes, and MLP-ANN classifiers were investigated and MLP-ANN was found to be the most effective classifier for home appliance identification. Even in the presence of extra white Gaussian noise, this system performed well with acceptable accuracy. There is a provision in the circuit to control the appliance(s) using a relay from a remote location.

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