Cross-Correlation Based Classification of Electrical Appliances for Non-Intrusive Load Monitoring

Soumyajit Ghosh, *Member, IEEE*
Department of Electrical Engineering, Jadavpur University, Kolkata 700032, West Bengal, India.
Email: soumyajit.ghosh@ieee.org

Deepak Kumar Panda
Department of Mathematics, College of Engineering Mathematics and Physical Sciences, University of Exeter, Penryn Campus, TR10 9FE, UK.
Email: dp457@exeter.ac.uk

Saptarshi Das, *Member, IEEE*
Department of Mathematics, College of Engineering Mathematics and Physical Sciences, University of Exeter, Penryn Campus, TR10 9FE, UK.
Email: saptarshi.das@ieee.org

Debashis Chatterjee
Department of Electrical Engineering, Jadavpur University, Kolkata 700032, West Bengal, India.
Email*:* debashisju@yahoo.com

***Abstract*—Over the last few decades, residential electrical load classification and identification have been one of the most challenging research in the area of non-intrusive load monitoring (NILM) for home energy management system. The application of NILM technique in the smart grid has gained enormous attention in recent years. Several methods, including information from the given domains into NILM, have been proposed. Recently, among these methods, machine learning techniques are shown to be significantly better based on large-scale data for load monitoring. In this paper, machine learning techniques are utilized for residential load classification on novel cross-correlation based features, which are extracted from the synthetic time series data. We also present a *t*-distributed stochastic neighbour embedding (*t*-SNE) based dimensionality reduction from the high dimensional feature set so that the classification can be implemented on a general-purpose microcontroller for near real-time monitoring. Our experimental results show that the extracted features are suitable for reliable identification and classification of different and the combination of residential loads.**

Keywords—Non-intrusive load monitoring, smart metering, classification, supervised machine learning.

I. Introduction

Electrical appliance monitoring has boundless implications in shaping the power grid technology, time of use (ToU) tariff setting, reduction of electricity bill, and improvement of energy efficiency [1], [2]. Since the last decade, various Government and other public sectors are strongly encouraging energy conservation as well as emission reduction. Due to the continuous growth of technology, the electricity demand for the end-user is increasing. Thus, efficient usage of electricity is a challenging area, which can be achieved with the deployment of smart grid technologies. Smart meters are an essential feature of the smart grid, as it provides complete information about residential electrical appliances' power consumption [3]. In recent times, the awareness of installing smart meters [4] in residential houses has grown widely in many countries. The next-generation smart metering technologies will require highly sophisticated monitoring methods.

Furthermore, the collaboration of Internet-of-Things (IoT) technologies with smart electricity meters have a high potential in bringing revolutionary changes by making every information available and accessible on the internet [5]. Such data can then be processed using machine learning techniques for consumer application. One of the effective techniques for finding and investigating electrical appliances information is called the non-intrusive load monitoring or NILM, which permits the individual appliance identification based on the aggregated data collected at a single point instead of mounting multiple voltage and current sensors [6]. According to state of the art, modified energy efficiency facility built on the NILM technology can lead to a roughly 14% decrease in the consumption of electricity usage for a given residence [7]. Thus, NILM is an innovative and cost-effective procedure for monitoring electrical loads.

A. Literature Review

NILM, an idea initially established by Hart [8], has enormous potential to revolutionize the field of electrical load monitoring [9], [10]. Feature extraction from raw signals is a crucial part of NILM. The machine learning techniques are applied on the extracted features to investigate the aggregated load current and determine the consumption of appliances from a single point of measurement [11],[12],[13],[14],[15]. After the load identification, the information is communicated to the utility and the consumers for framing the energy management policies [16]. Furthermore, consumers can also monitor their energy consumption according to the recommendations by utility providers [17]. A crucial step in NILM is training a supervised learning algorithm to build a classifier for identifying different classes as the electric appliances [18],[19],[20]. In order to validate the accuracy of different classifier models, researchers have proposed to create a large variation of NILM datasets containing voltage and current data of the electrical appliances under test.

There are three basic methods for NILM, event-based method, optimization-based and machine learning-based methods [21]. Event-based methods sense the ON/OFF events of electrical loads and categorize them by using the transient and steady-state variations of their features. This type of approach will monitor the current appliance state and obtain spontaneous results. However, these methods are inadequate for the appliances that have visible ON/OFF transients, thus requiring manually extracted features. Optimization-based technique [22] requires the highest possible combination of all loads whose resultant is close to the recorded data. This method tries to formulate the optimum energy disaggregation from the global possibility. The computational difficulty of most optimization-based technique increases simultaneously with the increase of loads. Recently, machine learning techniques have been widely utilized in smart grid decision making and demand response, utilizing the availability of big data and relevant signal processing techniques.

Similarly, for home energy management systems, machine learning methods apply to NILM. Both the classes of machine learning techniques, i.e. supervised and unsupervised learning, are applicable for NILM. Previously, it was shown that extracting suitable features for electrical appliances are useful for NILM, and the accuracy of classification is significantly improved [11]. Hidden Markov model (HMM) based load disaggregation has significant contribution in the field of NILM [23]. Other machine learning techniques such as neural networks, transfer learning [20], dictionary learning [18], decision tree [19] were also used for appliance classification.

B. *Contribution of This Paper*

This paper proposes a cross-correlation based features extraction followed by training supervised learning-based classifiers that can uniquely identify multiple electrical appliances in the residential sector. Features extraction is performed by using aggregate current measurements under varying load conditions. The high dimensional features, extracted from the current waveform time series data, have been visualized using *t*-SNE dimensionality reduction techniques. Then classification is performed on the extracted features using different classifier families, and benchmarking has been performed based on their performance on the given dataset using confusion matrices.

II. Description of Proposed NILM Technique

A. *Architecture of Proposed System*

A typical NILM technique description is shown in Figure 1. Usually, the NILM technique monitors multiple electrical appliances from a single point of measurement at the power panel in the residential sector. After that, information is extracted from each appliance's data with the help of their aggregated current waveforms. The system extracts the cross-correlation based features from the measured phase to phase currents. These features are used to identify or classify each load from aggregate current measurements. The electrical loads considered for the proposed study are frequently used in residential buildings. For lifts, usually, variable speed drives (VSD) are used. Other commonly used loads considered for the proposed study are television, personal computer, battery charger and dimming lamp. The schematic diagram for the proposed scheme is shown in Figure 1(a), and the per-phase equivalent circuit for the system is shown in Figure 1(b). The R_s and L_s before and after the point of common coupling (PCC) are considered as feeder resistance (R_s) and inductance (L_s) and cable resistance (R_L) and inductance (L_L) respectively.

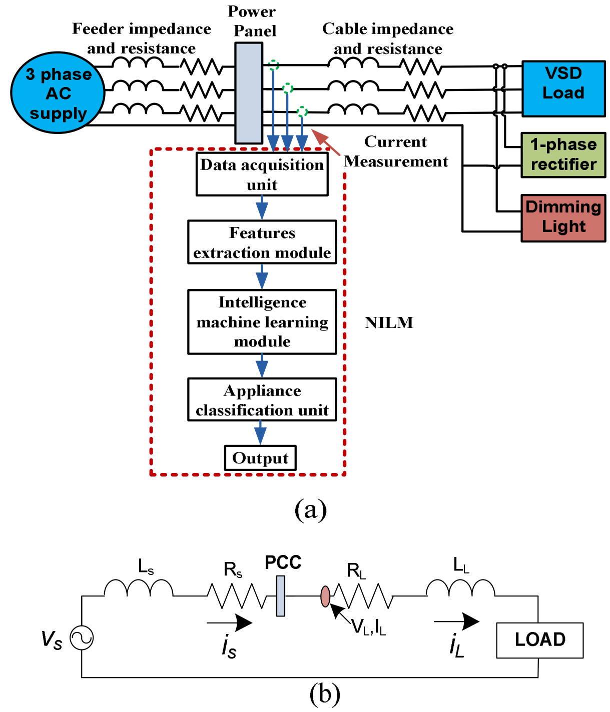

Figure 1: Proposed 3-phase four-wire connection of the residential electrical system. (a) schematic diagram (b) per phase equivalent circuit diagram.

B. *Features Extraction from Current Signature Waveforms using Cross-Correlation Based Techniques*

Cross-correlation is a measure which closely relates to the convolution of two signals. Correlation techniques for feature extraction can be of two types: auto-correlation and cross-correlation. The correlation technique finds out the similarity between two signals. It captures the measurable evidence about the temporal correlation structures between two signals in terms of correlograms. It has been widely used in signal and image processing for pattern classification. In cross-correlation, two dissimilar signals are compared to measure their similarity, while autocorrelation is a measure of the signal with its own lagged versions. In order to extract features from the signal, both cross-correlation and autocorrelation can be used. In the existing literature, it has been shown that the correlation technique can extract relevant features from the current signal for faults classification [24]. Using this technique for electrical appliances can be useful for NILM and load classification. In this proposed technique, it is observed that the cross-correlation based feature extraction method gives much better performance as compared to that of the autocorrelation based features extraction methods. One advantage of the cross-correlation technique is that it reduces the arbitrary uncorrelated noise, present in the signal.

The cross-correlation of two different sequences $a(n)$ and $b(n)$ is shown as:

$$P_{ab}[m] = \left\{ \begin{array}{l} \sum_{n}^{N-m-1} A_{n+m} B_n, m \geq 0 \\ P_{ab}(-m), m < 0 \end{array} \right\}. \tag{1}$$

The index m signifies time shift or lag operator and P_{ab} designates the cross-correlation sequences. Here, N represents the total number of samples, and the resultant cross-correlation sequence is ($2N$-1). From each cross correlogram, different sets of features are extracted depending on the specific problem. In this paper, different types of appliances' current waveform combinations are studied using cross-correlation metrics.

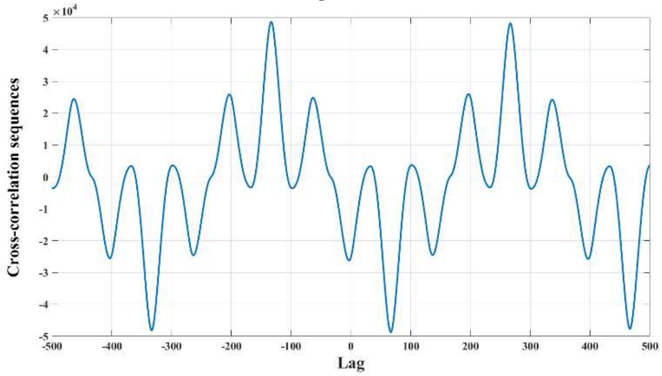

Figure 2: Cross-correlogram of a VSD phase A and phase B, where an asymmetric pattern is observed for the unbalanced 3-phase load.

For the given NILM problem, a combination of appliances are used, and the data is collected based on their switched status. The useful features are extracted from the cross-correlogram of each combination of appliances that are working together. For convenience, P_n it is considered as a n^{th} cross-correlation sequence of a specific load identification. Figure 2 shows a typical cross-correlogram of a VSD phase A and phase B signal. In this proposed non-intrusive appliance identification technique, twelve features are extracted from each cross-correlogram. The features that are extracted are given as:

X_1 = Maximum value of cross-correlation sequence;

X_2 = Index of the maximum value;

$$X_3 = \sum_{n=-N}^{N} n.P_n \Big/ P_{\max} = \text{Equivalent width of the correlogram;}$$

$$X_4 = \sum_{n=-N}^{N} n.P_n \Big/ \sum_{n=-N}^{N} P_n = \text{Centroid of the correlogram;}$$

$$X_5 = \sum_{n=-N}^{N} |n|.P_n \Big/ \sum_{n=-N}^{N} P_n = \text{Absolute centroid;}$$

$$X_6 = \sqrt{\sum_{n=-N}^{N} n^2.P_n \Big/ \sum_{n=-N}^{N} P_n} = \text{Root mean square width;}$$

$$X_7 = \sum_{n=-N}^{N} P_n \big/ (2N+1) = \text{Mean value of the correlogram;}$$

$$X_8 = \sqrt{\sum_{n=-N}^{N} (P_n - X_7)^2 \Big/ (2N+1)} = \text{Standard deviation;}$$

$$X_9 = \sum_{n=-N}^{N} (P_n - X_7)^3 \Big/ 2N(X_8)^3 = \text{Skewness;}$$

$$X_{10} = \sum_{n=-N}^{N} (P_n - X_7)^4 \Big/ 2N(X_8)^4 = \text{Kurtosis;}$$

$$X_{11} = \sum_{n=-N}^{N} (\bar{b} - b)^2 \Big/ (2N+1) = \text{Variance of phase B current;}$$

$$X_{12} = \sum_{n=-N}^{N} (\bar{b} - b)^4 \Big/ 2N(b_s)^4 = \text{Kurtosis of phase B current;}$$

where $\bar{b}$ = mean value of b and b_s is the standard deviation of the signal b. These twelve extracted features represent the maximum value of the cross-correlogram sequence, index of maximum value, equivalent width, centroid, absolute centroid, root mean square width, mean value, standard deviation, skewness, kurtosis of cross-correlogram sequence, variance and kurtosis of the phase B current respectively. Some prior experience is helpful for features selection of such problems.

III. Supervised Learning Methods for Non-Intrusive Load Classification

The classification model is based on the features, extracted from the raw current signal at the entry point of a residential system. The given task is to disaggregate the loads and classify them into different classes. The dataset is randomly split equally into training and testing sets. Each family of machine learning algorithms are trained and cross-validated on the training and testing dataset, respectively, and their relative performances are compared. Six supervised learning models are used here viz. logistic regression (LR), decision tree (DT), multi-layer perceptron (MLP), k-nearest neighbours (k-NN), gradient boosting (GB), random forest (RF). The classifier is trained based on the features extracted from the current waveform cross-correlograms to identify the nature of the load in a non-intrusive fashion. In addition, hyper-parameter tuning in each family helps to get better classification accuracy by adjusting a certain set of parameters/knobs of the algorithm. The hyperparameters are shown in Table I to Table VI for the six families of classifiers as described in the Scikit-learn package in Python [25], which provides a robust implementation for a wide range of machine learning problems.

A. *Logistic Regression Classifier*

Logistic regression is a supervised machine learning algorithm that uses a logistic function to model dependent variables. Since this is a multi-class classification problem, multinomial logistic regression has been used. The hyperparameter used for this classifier is shown in Table I.

TABLE I. Hyper-parameters for Logistic Regression

Logistic regression			
Penalty	L_2	Solver	lbfgs
Dual	False	Maximum iteration	100
Tolerance for stopping criteria	1e-4	Multi class	Auto
Inverse of regularization strength	1.0	Verbose	0
Fit intercept	True	Warm start	False
Intercept scaling	1	N_{jobs}	None
Class weight	None	l_1 ratio	None
Random state	None		

B. *Decision Tree Classifier*

Decision tree algorithm uses a predictive model in the form of a tree ranging from the input data to the discrete output observations which are used in classification. The hyperparameter used for the proposed classification is shown in Table II.

TABLE II. HYPER-PARAMETERS FOR DECISION TREE

Decision tree			
Criterion	Gini	Max features	None
Splitter	Best	Min impurity decrease	0
Max depth	None	Min impurity split	None
Min samples split	2	Class weight	None
Min samples leaf	1	Presort	Deprecated
Min weight fraction leaf	0	Ccp alpha	0.0
Random state	None	Max leaf nodes	None

C. Multi-Layer Perceptron Classifier

Multi-layer perceptron classifier is built with a class of feedforward artificial neural network consisting of input, hidden and output layer used for classifying the input data. The hyperparameter used for the proposed classification is shown in Table III.

TABLE III. HYPER-PARAMETERS FOR MULTI-LAYER PERCEPTRON

Multi-layer perceptron			
Hidden layer sizes	100	Power t	0.5
Activation	ReLU	Max iteration	200
Solver	Adam	Shuffle	True
Alpha	0.0001	Random state	None
Batch size	Auto	Tolerance for stopping criteria	1e-4
Learning rate	Constant	Verbose	False
Learning rate init	0.001	Warm start	False
Momentum	0.9	Nesterovs momentum	True
Early stopping	False	Validation fraction	0.1
Beta 1	0.9	Beta 2	0.999
Epsilon	1e-8	N iter no change	10
Max fun	15000		

D. k-nearest Neighbors (k-NN) Classifier

The *k*-nearest neighbors classifier is a non-parametric method, for instance-based learning where the classification is performed with the help of the label assigned to the nearest data points. The hyperparameter used for the proposed classification is shown in Table IV.

TABLE IV. HYPER-PARAMETERS FOR K-NEAREST NEIGHBORS

Decision tree			
N neighbors	5	P	2
Weights	Uniform	Metric	Minkowski
Algorithm	Auto	Metric params	None
Leaf size	30	N jobs	None

TABLE V. HYPER-PARAMETERS FOR GRADIENT BOOSTING

Gradient boosting			
Loss	deviance	Max leaf nodes	none
N estimators	100	Presort	deprecated
Subsample	1.0	Validation fraction	0.1
Criterion	Friedman mse	Ccp alpha	0
Min samples split	2.0	Tol	1e-4
Min samples leaf	1.0	Verbose	0
Min weight fraction leaf	0	Warm start	false
Max depth	3	Max features	none
Min impurity decrease	0	Validation fraction	0.1
Min impurity split	none	N iter no change	none
Init	none		

E. Gradient Boosting Classifier

Gradient boosting classifier is an ensemble of weak prediction models which mainly consists of decision trees. The hyperparameter used for the classification purpose is shown in Table V.

F. Random Forest Classifier

Random forest is a classifier model that combines an ensemble of multiple decision trees. The classifier is trained on the mean or mode results of the multiple estimators involved. The hyperparameter are shown in Table VI.

TABLE VI. HYPER-PARAMETERS FOR RANDOM FOREST

Random forest			
Criterion	Gini	Max features	Auto
N estimators	100	Min impurity decrease	0
Max depth	None	Min impurity split	none
Min samples split	2	Class weight	none
Min samples leaf	1	Bootstrap	true
Min weight fraction leaf	0	Ccp alpha	0.0
Random state	None	Max leaf nodes	None
Oob score	False	N jobs	none
Verbose	0	Warm start	false
Max samples	None		

IV. RESULTS AND DISCUSSIONS

This paper has two important sections. Firstly, feature extraction from the aggregated current waveforms and secondly classification of different electrical appliances using the extracted feature. Cross-correlation based feature extraction of different electrical loads along with different supervised learning technique is used here for load classification. Three frequently used residential electrical loads are used for the proposed system viz. VSD load, single-phase rectifier load and dimming light load.

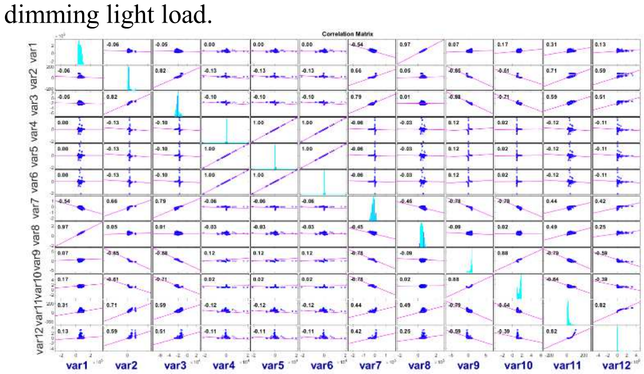

Figure 3: Correlation matrix plot of all loads acting together.

Here, correlation-based feature extraction is used for the supervised learning algorithms. The extracted features may be correlated amongst themselves, thus adding some degree of redundancy in the feature space and also affecting the classifier's performance. The multivariate correlation structure amongst the feature pairs is shown as the correlation matrix. The correlation matrix of the five classes are shown in Figure 3-Figure 7 for the five classes viz. 1) all the loads are acting together, 2) VSD loads with rectifier load, 3) VSD loads with dimming light load, 4) VSD load, 5) dimming light with rectifier load respectively. From the correlation matrix, we get an insight into the highly correlated variables. In the correlation matrix, the feature scatterplots with linear pattern show high correlation for those pairs and the diagonal display histograms of each attribute. Here, a few cases showed strong nonlinear structure, e.g. Figure 4 and Figure 6 for VSD load.

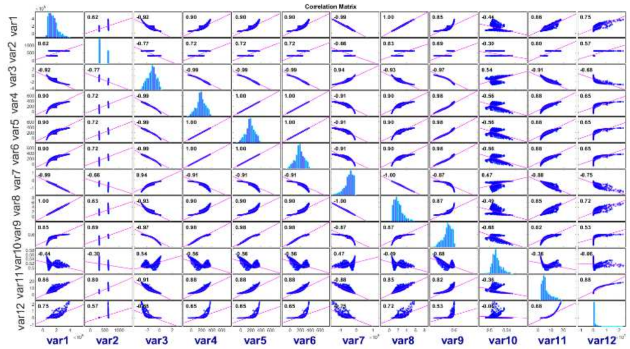

Figure 4: Correlation matrix plot of VSD with rectifier load.

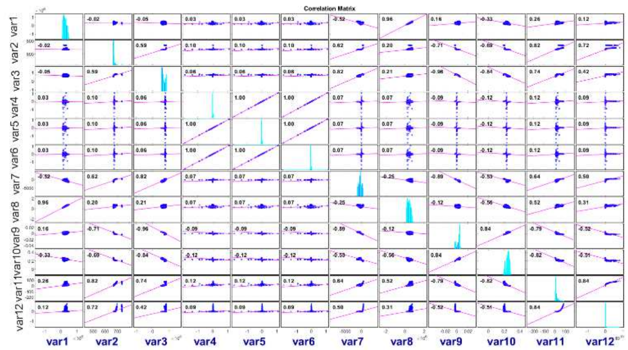

Figure 5:Correlation matrix plot of VSD with dimmer load

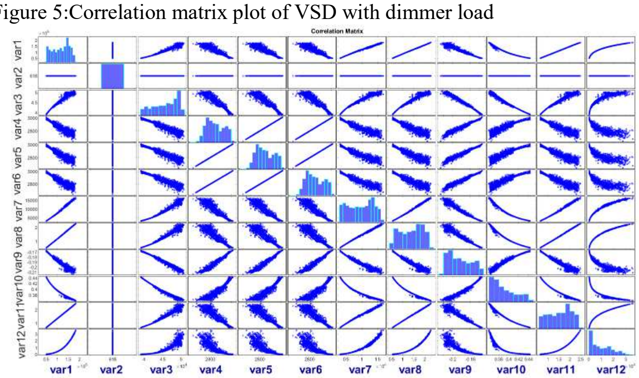

Figure 6: Correlation matrix plot of VSD load.

The *t*-SNE is a nonlinear dimensionality reduction technique used for visualization of multi-dimensional data. It transforms the variables in higher dimensions to lower dimensions for visualization. Unlike principal component analysis (PCA), it is a nonlinear transformation. A major problem in PCA is that they are built for linearly correlated data and some information gets lost when projected on lower dimensions. Nonlinear manifold learning methods are utilized in *t*-SNE. An illustrative example of the *t*-SNE plot is shown in Figure 8 on the correlation-based extracted features for four different perplexity values for the five different classes. It is observed from Figure 8 that the classes are represented as a complex non-overlapping cluster as the perplexity is increased. The shape of the clusters also differ with distance (Euclidean), optimizer, perplexity and are harder to interpret in the projected lower-dimensional space but conveys that they can be eventually classified using suitable algorithms.

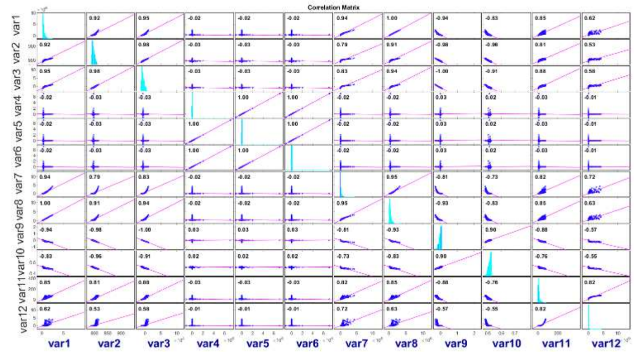

Figure 7: Correlation matrix plot of dimming light with rectifier load.

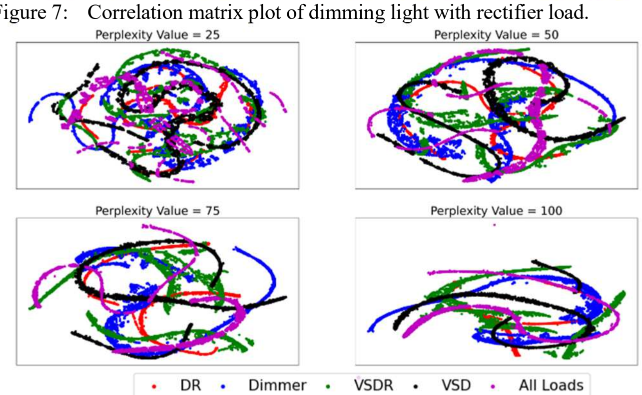

Figure 8: The *t*-SNE reduced dimensional plots for the 5 load classes. (Red-Dimmer Rectifier Blue- VSD+Dimmer, Green-VSD+Rectifier, Violet-VSD, Pink- All Loads)

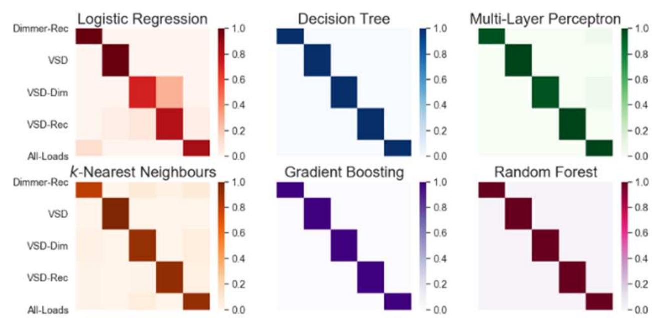

Figure 9: Confusion matrices using 6 different classifiers.

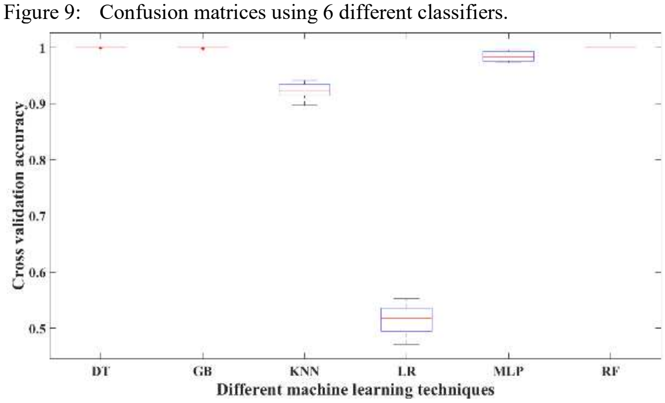

Figure 10:. Cross-validation accuracy of proposed load classification technique.

Confusion matrices are widely used for quantifying classification accuracy in NILM. While observing the confusion matrix in Figure 9, it is clear that the lowest accuracy is obtained for the logistic regression classifier (~50%). Lower accuracy is achieved when VSD with dimming light load, VSD with single-phase rectifier load and all loads acting together creates confusion amongst each other. The decision tree and gradient boosting methods, *k*-NN and MLP classifiers achieve an accuracy of 99%, 92% and 98% respectively.

The cross-validation accuracy for different machine learning algorithm is performed to determine optimal performance for the classifier. A 10-Fold cross-validation test is applied for benchmarking the accuracy. In the *K*-fold cross-validation test, a single set of data is used for testing and remaining (*K*-1) subsets of data are used for training purpose in a cyclic manner. The box plot of accuracies using different classifiers are shown in Figure 10. It can be concluded from the boxplots that the random forest algorithm achieves 100% classification accuracy which is the best performance amongst the six classifiers beside decision tree and gradient boosting, as all of them yield low variance across the 10-fold cross-validation.

V. Conclusion

This paper introduces a concept of correlation-based features extraction along with supervised learning techniques for classification of the residential appliances. Firstly, features are extracted from the current waveforms. The purpose is to classify the appliances in a non-intrusive fashion using cross-correlation based features which give high accuracy. In this paper, a sample model has been implemented with a laboratory prototype dataset. Here, six classifiers are employed, and a comparative study is carried out in terms of accuracies of 10-fold cross-validation. Additionally, the system can also operate automatically in a more efficient manner with minimum maintenance cost. The cross-correlation based features extraction technology can be embedded with future smart metering technology. With the vast deployment of cost-effective residential smart meters and upcoming big data technologies, accurate identification/classification information for appliances will become accessible. This information will help both utility and consumer for further novel applications. Future scope for the study includes the extension to a greater number of loads and the distinction of similar loads.

Acknowledgement

SG was supported by the Visvesvaraya PhD scheme, Government of India, awardee no. VISPHD-MEITY-1431.

References

[1] "Advanced Metering Infrastructure - India Smart Grid Knowledge Portal." [Online]. Available: www.indiasmartgrid.org

[2] D. Murray, L. Stankovic, V. Stankovic, and N. Espinoza-Orias, "Appliance electrical consumption modelling at scale using smart meter data," *Journal of Cleaner Production*, vol. 187, pp. 237–249, 2018.

[3] S. Ghosh, A. Chatterjee, and D. Chatterjee, "Improved non-intrusive identification technique of electrical appliances for a smart residential system," *IET Generation, Transmission & Distribution*, vol. 13, no. 5, pp. 695–702, 2018.

[4] F. Luo, G. Ranzi, W. Kong, Z. Y. Dong, S. Wang, and J. Zhao, "Non-intrusive energy saving appliance recommender system for smart grid residential users," *IET Generation, Transmission & Distribution*, vol. 11, no. 7, pp. 1786–1793, 2017.

[5] E. Spanò, L. Niccolini, S. Di Pascoli, and G. Iannacconeluca, "Last-meter smart grid embedded in an Internet-of-Things platform," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 468–476, 2014.

[6] M. Dong, P. C. Meira, W. Xu, and W. Freitas, "An event window based load monitoring technique for smart meters," *IEEE Transactions on Smart Grid*, vol. 3, no. 2, pp. 787–796, 2012.

[7] C. Fischer, "Feedback on household electricity consumption: a tool for saving energy?," *Energy Efficiency*, vol. 1, no. 1, pp. 79–104, 2008.

[8] G. W. Hart, "Non-intrusive appliance load monitoring," *Proceedings of the IEEE*, vol. 80, no. 12, pp. 1870–1891, 1992.

[9] S. B. Leeb, S. R. Shaw, and J. L. Kirtley, "Transient event detection in spectral envelope estimates for non-intrusive load monitoring," *IEEE Transactions on Power Delivery*, vol. 10, no. 3, pp. 1200–1210, 1995.

[10] L. K. Norford and S. B. Leeb, "Non-intrusive electrical load monitoring in commercial buildings based on steady-state and transient load-detection algorithms," *Energy and Buildings*, vol. 24, no. 1, pp. 51–64, 1996.

[11] H. Liu, H. Wu, and C. Yu, "A hybrid model for appliance classification based on time series features," *Energy and Buildings*, vol. 196, pp. 112–123, 2019.

[12] A. Miyasawa, Y. Fujimoto, and Y. Hayashi, "Energy disaggregation based on smart metering data via semi-binary nonnegative matrix factorization," *Energy and Buildings*, vol. 183, pp. 547–558, 2019.

[13] Y. Liu, X. Wang, L. Zhao, and Y. Liu, "Admittance-based load signature construction for non-intrusive appliance load monitoring," *Energy and Buildings*, vol. 171, pp. 209–219, 2018.

[14] N. Sadeghianpourhamami, J. Ruyssinck, D. Deschrijver, T. Dhaene, and C. Develder, "Comprehensive feature selection for appliance classification in NILM," *Energy and Buildings*, vol. 151, pp. 98–106, 2017.

[15] K. Basu, V. Debusschere, A. Douzal-Chouakria, and S. Bacha, "Time series distance-based methods for non-intrusive load monitoring in residential buildings," *Energy and Buildings*, vol. 96, pp. 109–117, 2015.

[16] J. Alcalá, J. Ureña, Á. Hernández, and D. Gualda, "Event-based energy disaggregation algorithm for activity monitoring from a single-point sensor," *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 10, pp. 2615–2626, 2017.

[17] Y. Liu, G. Geng, S. Gao, and W. Xu, "Non-intrusive energy use monitoring for a group of electrical appliances," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3801–3810, 2016.

[18] V. Singhal, J. Maggu, and A. Majumdar, "Simultaneous detection of multiple appliances from smart-meter measurements via multi-label consistent deep dictionary learning and deep transform learning," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 2969–2978, 2018.

[19] M. S. Piscitelli, S. Brandi, and A. Capozzoli, "Recognition and classification of typical load profiles in buildings with non-intrusive learning approach," *Applied Energy*, vol. 255, p. 113727, 2019.

[20] Y. Liu, X. Wang, and W. You, "Non-Intrusive Load Monitoring by Voltage-Current Trajectory Enabled Transfer Learning," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5609–5619, 2018.

[21] H.-H. Chang, "Non-intrusive demand monitoring and load identification for energy management systems based on transient feature analyses," *Energies*, vol. 5, no. 11, pp. 4569–4589, 2012.

[22] K. He, D. Jakovetic, B. Zhao, V. Stankovic, L. Stankovic, and S. Cheng, "A generic optimization-based approach for improving non-intrusive load monitoring," *IEEE Transactions on Smart Grid*, vol. 10, no. 6, pp. 6472–6480, 2019.

[23] W. Kong, Z. Y. Dong, D. J. Hill, J. Ma, J. Zhao, and F. Luo, "A hierarchical hidden Markov model framework for home appliance modeling," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3079–3090, 2016.

[24] S. Dalai, B. Chatterjee, D. Dey, S. Chakravorti, and K. Bhattacharya, "Rough-set-based feature selection and classification for power quality sensing device employing correlation techniques," *IEEE Sensors Journal*, vol. 13, no. 2, pp. 563–573, 2012.

[25] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, and others, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.