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Real Time Identification of Electrical Devices through Power Consumption Pattern Detection

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***Abstract* — This research discusses a way to identify electrical devices in real time using intelligent techniques through data analysis. The electrical device identification process is initiated by collecting information related to power consumption of electrical appliances which are used in domestic life. A prototype data acquisition system was implemented to extract parameters such as active power, reactive power, phase shift, root mean square voltage and current from the appliances connected to it. The analysis is done using neural networks, support vector machines, k-means, mean-shift and silhouette classifiers. The purpose of this study is to select the best classifier which produces the optimum results in detecting and identifying electrical appliances in real time from their electric parameters. The selected classifier is used to determine a power consumption pattern (signature) for different electric appliances.**

Keywords - classification, clustering, k-means, mean-shift, neural networks, silhouette, support vector machines

I. INTRODUCTION

As an intelligent approach, machine learning techniques can be used to understand the meaning of a data set in a logical way and provide useful outputs from raw data for different purposes. In this research, a few supervised and unsupervised learning methods are compared with a constant data set and a better classifier is chosen for the data clustering and prediction. In considering power consumption patterns, neural networks and support vector machines were used as supervised learning methods to classify data and predict patterns. Basically, the real time electrical device identification is done by comparing the power consumption features of each device with the other devices and clustering the data sets in the training period and predicting the electrical device connected to the system with a new data set.

Here the main variables considered in this research are active power, reactive power, phase shift, root mean square voltage and current. The data collection is done covering all the modes of operations and all the statuses of each electrical device in order to get a fully understanding about the behavior of their functionality. The purpose is to train the system to identify the electrical device in any moment of their cycle of functioning. The challenging factor that was seen in the research is to understand and collect data for the complete cycle containing all the statuses acquired by the electrical device. In the realization of the actions of a particular device, data has to be collected covering all the scenarios as far as the performance of a particular device is considered.

II. RELATED WORK

A device called smart plug is created to detect the power consumption from each device. And the smart plug identifies each device using machine learning techniques and classifies data for further analysis [2], [3], [1]. There are many researches done to detect electrical devices in real time and some different researches were done to optimize and predict the power consumption [4], [5], [6], [7]. Here both these scenarios are addressed in order to provide an advanced overview on power consumption at domestic level in Sri Lanka. There are researches done to detect electrical devices in real time to collect data with better classification in the earlier stages of data acquisition to provide a solid foundation for data analysis purposes [14]. Later on neural networks and classification algorithms are used to detect consumption patterns and identify and cluster the electrical devices in purpose of real time device identification. In the electrical device identification domain, the related researches were more focused on extracting data from many devices and classifying them [16]. In understanding and classifying the electrical devices, there are limited numbers of features that can support the task [17]. Here the main attention was paid to the active power consumption. When it comes to devices which are consuming similar amount of power, this factor is not enough to classify the devices. In this case more features were considered to support the classification task [20]. These features are reactive power, phase shift, root mean square voltage and current.

- Support Vector Machines.
- Artificial Neural Networks.
- K-Means Classification.
- Silhouette Classification.
- Mean-Shift Classification

In considering the machine learning algorithms used in the research, the reason for choosing a number of algorithms is that the way these algorithms converge to a result is different from each other as far as the research objective is considered. The support vector machines were not used in most of the researches done in the electrical device identification. Most of the time the artificial neural networks [9] were used to perform the clustering and identification tasks. Support vector machine algorithm [8], [18], [19] was

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found to be a faster algorithm which converges to the results as far as many other tests were done in classifying data. General theory of working in support vector machines is not very complex and it enables in predicting the cluster of a new data set with the aid of an earlier trained data set.

The k-means algorithm [10], [15] is a very powerful self-learning algorithm. This algorithm needs only the input of a data set with the expected feature vector. The algorithm itself classifies the groups and provides the clustered output. This algorithm is really useful when predicting the electrical device which is providing a newer data set when it is in action with the data acquisition system. The Silhouette [12] [13] algorithm has the capability of showing graphical outputs from the clustering results. As far as supervision is considered, this is also an unsupervised learning method. Mean shift [11] algorithm also functions based on the mean distance from a particular data point to the other clusters.

III. RESULTS AND DISCUSSION

In this section the way that the data was analyzed and related challenges in identifying the factors which govern the uniqueness of electrical devices will be discussed. Every electrical device possesses its own signature as far as the power consumption is considered.

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A. *Electrical Device Identification*

In analyzing the power consumption in domestic level, the data extraction from devices separately provides more detailed view of consumption. There are main factors that have to be considered, before creating a mathematical model to analyze data.

- Multi-Mode Functionality – The complex behavior in certain devices like fan, iron, washing machine, refrigerator possesses different modes of action.
- Parallel usage of devices.
- External effect – The data acquisition must act in a constant manner depending on the external factors like temperature, electromagnetic interference, communication failures, etc.
- Load variation needs to be handled based on the given scenario.

B. *Supervised Learning*

In the analysis, support vector machines (SVM) and artificial neural networks (ANN) are mainly used. In usage of SVM and ANN, a data set obtained from the data acquisition system was used for the training of these algorithms. When considering the main parameters that are considered for device classification; active power, reactive power, Vrms, Irms and phase shift, it is clear that there is a unique signature for each electrical device. In the first place, selecting five parameters for device identification enables the avoiding a difficulty in identifying devices with similar power consumption and multiple mode of operation. By means of acquiring a data set for a longer time period, a supervised algorithm like support vector machines can be trained by providing the dataset and the matching device. Here for each state of the device a unique number is used to represent each device.

TABLE I. SAMPLE DATA SET

Active Power	**Reactive Power**	**V_{rms}**	**I_{rms}**	**Phase Shift**	**Device Name**
59.13	63.00	232.60	0.27	0.94	Bulb
751.33	752.00	210.82	3.57	1.00	Toaster
63.66	64.60	228.71	0.28	0.99	Fan
211.02	237.00	225.77	1.05	0.89	Blender

TABLE II. ACCURACY OF CLASSIFICATION

Type	**Classifier**	**Accuracy (%)**	**Execution (s)**
Supervised	SVM	97	0.010
Supervised	ANN	96	13.000
Unsupervised	Mean Shift	94	0.013
Unsupervised	Silhouette	98	0.012
Unsupervised	K-Means	98	0.15

C. *Unupervised Learning*

In unsupervised learning the output group is decided by the algorithm itself. The only input to the algorithm is a training data set and it clusters the inputs by itself. In this k-means, mean-shift and silhouette algorithms were used to test the data set and classify them. The k-means and silhouette algorithms provide higher accurate results than other two algorithms. The mean-shift algorithm deviates from higher accuracy, when the number of devices gets increased in the data set. Silhouette classifier works with higher accuracy and it provides graphically the nature of the classification very clearly than other methods.

In the experiments, different electric devices were tested for different amounts of time and the expected prediction from each algorithm was recorded. Here the fast responses came from the SVM, silhouette and k-means algorithms. Figure 1 shows the outputs obtained from the classification from the silhouette algorithm. Here 14 different devices are shown and how these devices were classified can be seen. In addition to this algorithm the k-means algorithm was used to analyze how these devices are being classified when the five features are considered.

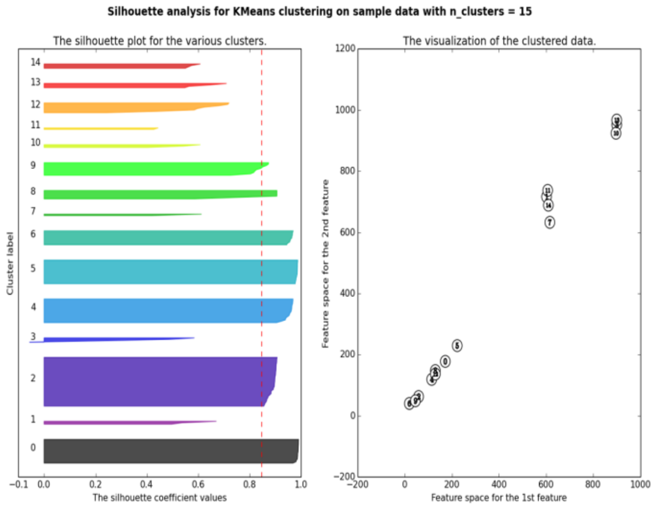

Figure 1. Classification Using Silhouette Algorithm

IV. Data Set Analysis

Even though there are five parameters which can enable a clear classification, the behavior of an electric device changes depending on couple of factors. Electrical devices change the power consumption depending on the mode of its operations. For instance a refrigerator consumes less power when the temperature inside the device is in the expected range and when the temperature increases due to door opening, the refrigerator again starts to cool and consume more power. In order to identify a particular electric device, there has to be a data set which has a full cycle of the power consumption regarding all features; active power, reactive power, Vrms, Irms and phase shift. Without the knowledge of a full cycle, the prediction of a particular electric device may be limited to a certain range.

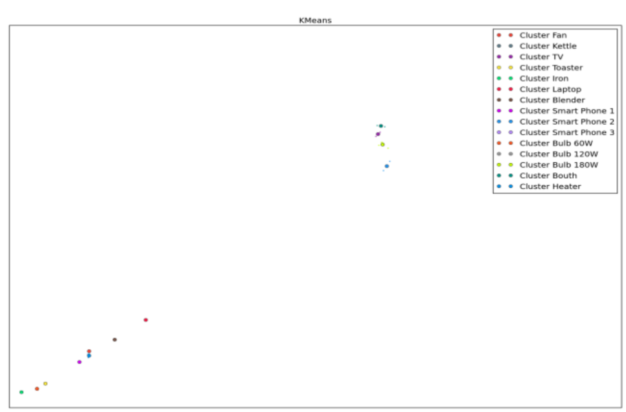

Figure 2. Classification Using K-Means Algorithm

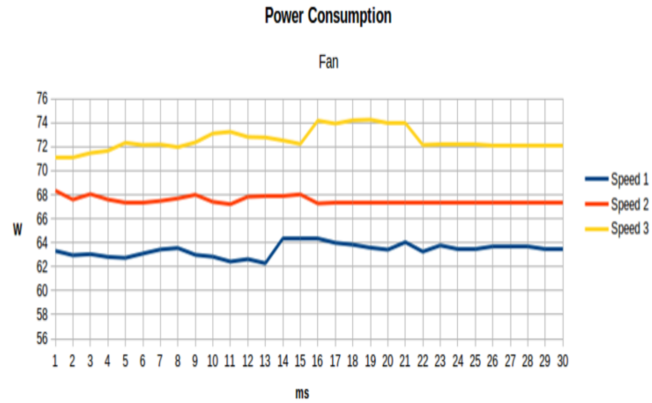

Figure 3. Multiple Modes of Operation of Fan

In this case, a complete analysis was done for the purpose of covering a full cycle of operation for each electric device. For each device there is a different way of power consumption based on use inputs. Considering a fan which has three different speeds of operation, data was collected for all modes of operation.

A. Test Results

From the data collected and the prediction experiments, it was clear that to identify an electrical device with a higher accuracy the modes of operations and complete functional cycle of each electrical device must be learned by the algorithm. Most of the electric devices with simple range of performance can be easily identified. But devices with complex modes of operations need to be tested and trained for the algorithm for a considerable amount of time to get accurate results. The main observations in the tests were that for each electric device there is its own way of acquiring power which can be identified as a cycle of performance.

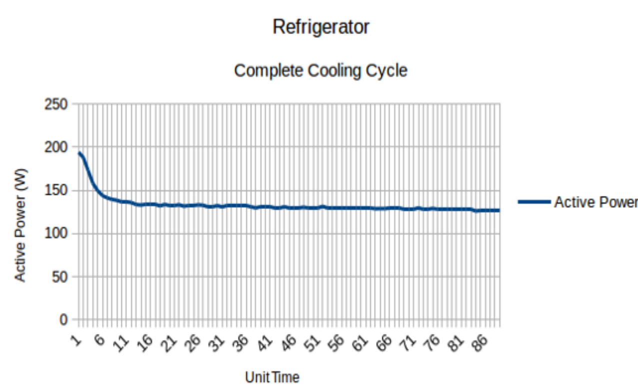

Figure 4. Active Power Consumption Cycle of Refrigerator

In identifying an electrical device, the main thing is to find a way of differentiating it from the other devices. The existence of a cycle helps to understand the behavior of an electric device in different phase of its complete cycle. Without understanding the full cycle, predicting or real time detection of an electrical device is not accurate. Here in the research, many devices which are used at household were tested and the cycles were plotted. It was obvious that when the data set covers more amount of the cycle the prediction results were accurate.

In the training process, initially the system is fed with sample data set containing the main parameters and the matching electrical device identity. Here there are two matrices known as the feature vector and corresponding output vector. These two vectors are being fed to the classifiers. In support vector machines and artificial neural networks, these two vectors are identified and learned. In support vector machines the kernel function is used to classify the data with reference to the data set. Here basically the sigmoid and the linear kernels were used when the support vector machines were used. Basically the python programming language was used to develop the model and do the classification task in a raspberry pi environment using Linux.

The figures showing the cycle of a refrigerator when completing its cooling cycle on the basis of increasing the temperature above the threshold value to keep the device in cooled condition and stop cooling after acquiring the threshold temperature. In detecting this device in any moment of its performance cycle, the system has to be trained on this complete data set. The main features active power, reactive power, phase shift, root mean square voltage and current behaves in a different way as far as test results were considered for many electrical devices.

When considering an electric device like television, it doesn't have a well-defined cycle, the cycle changes based on the human inputs, the power consumption changes when the volume increases, decreases, etc.

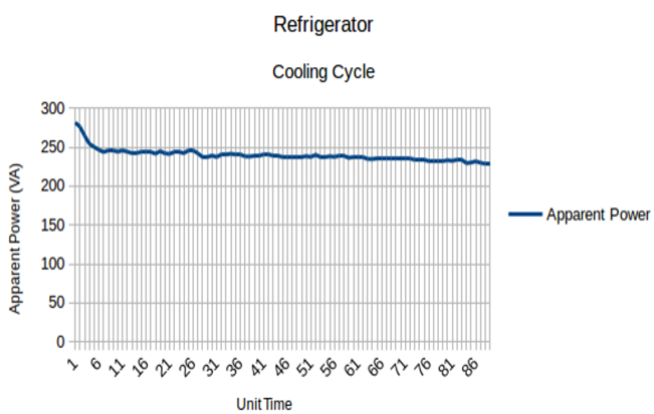

Figure 5. Reactive Power Consumption Cycle of Refrigerator

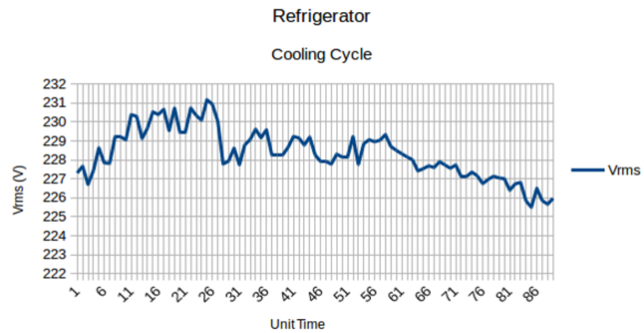

Figure 6. Root Mean Square Voltage Variation of Refrigerator

In the case of configuring the modes of operations like sound equalizer options, brightness, contrast and many more features, the power consumption changes. It is obvious for the fact that even when changing the channels, the power consumption is different from channel to channel when the cable televisions were tested in the research.

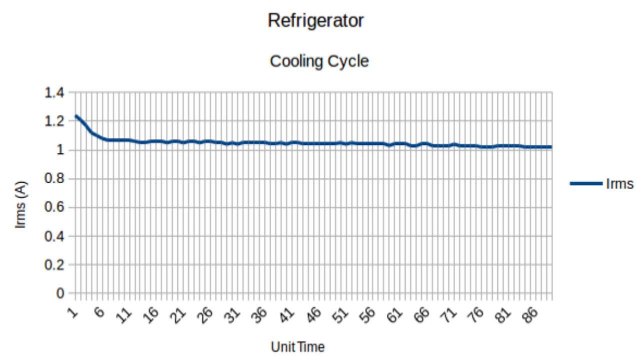

Figure 7. Root Mean Square Current Variation of Refrigerator

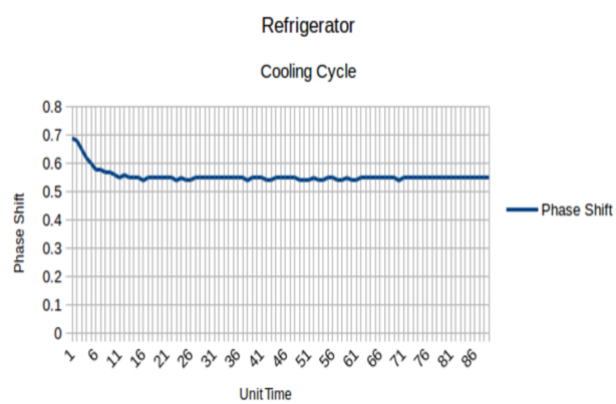

Figure 8. Phase Shift Variation of Refrigerator

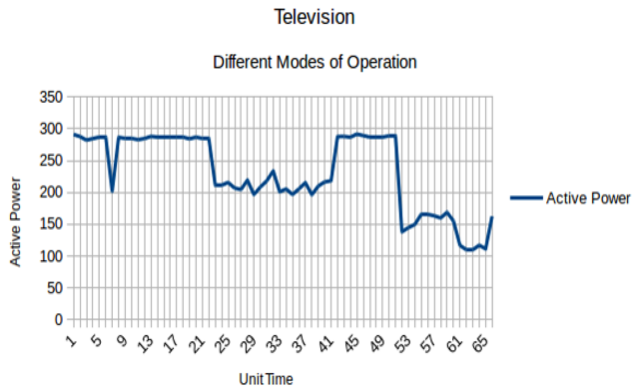

Figure 9. Active Power Variation of Television

These actions have to be trained for a longer period to detect an electric device like this. Here the number of modes of operation in such a device is very complex and really hard to be understood without a data set collected for a longer time period. An electrical appliance like laptop has more complex configurations.

V. Conclusion

By the data collected and patterns detected, it is clear that there is a unique signature for each electrical appliance and these signatures can be used to identify each device uniquely with a promising accuracy. This provides the opportunity to filter power consumption data from overall consumption data. In addition to that, each device has its way of functioning based on human involvement. It provides different modes of operation of devices. Each electrical device possesses its own cycle of power consumption.

For accurate identification of an electrical device, there has to be a complete set of data covering the full cycle. For devices like mobile phones, heater, fan, iron, oven and single or limited mode machines have a higher accuracy in detected by the system. For the complex mode operation devices like computer, laptop, radio and similar devices, the training is the most important thing to be done for a longer period.

The time period is important because when the devices are used for a longer period for the experiment, the capability of covering all the forms of actions and states taken by the device can be identified. Basically every electric device possesses its own unique signature. This unique signature identification is the key to identify an electric device with higher accuracy. Furthermore, in the case of understanding a device for the real time detection, the main thing is to identify the patterns of its functionality as far as whole cycle of performance is considered. The signature is also unique from one user to another user.

In addition to this the user profiling is also a possible output from this research. The research data presented in this paper is regarding the electrical devices which were mostly used in Sri Lanka. The profiling task is same for a different country. The only change is the change that has to be done in the data acquisition system for acquiring data in different voltage levels.

In the training process, the most vital task is to train the devices meeting different scenarios. For instance a refrigerator was tested for different amount of food storage and changing the number of times foods are being taken from the refrigerator in detecting every possible way of power consumption. More the experiment is done on different scenarios the accuracy of the results is higher.

The possibility of recognizing power consumption based on patterns or signatures for electrical appliances would be vital for intelligent power electronic systems for optimizing their power consumption as well as to detect and monitor connected services.

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