Detecting Unknown Electrical Loads using Open Set Recognition

1st Dániel István Németh
Faculty of Information Technology and Bionics
Pázmány Péter Catholic University
Budapest, Hungary
0000-0002-5740-284X

2nd Kálmán Tornai
Faculty of Information Technology and Bionics
Pázmány Péter Catholic University
Budapest, Hungary
0000-0003-1852-0816

***Abstract*—This paper presents a solution to the problem of detecting unknown electric loads in a household. With the emergence of renewable energy sources, the balancing of electricity production and demand has become more challenging, and control of the demand-side of the grid is needed. This requires knowledge about the load composition and control of the loads. For this task, knowledge about the loads is required. The problem with current load classification solutions is the closeness of the classification. Most smart plugs on the market cannot detect the loads. Moreover, the load classification solutions available in the literature lack the ability to detect if a previously unseen load is connected. We present a novel solution to this problem by applying an SVM-based Open Set recognition method to a load classification solution with already demonstrated results.**

***Index Terms*—smart plug, load classification, support vector machines, open set recognition, smart grid**

I. Introduction

With the increase in renewable energy sources, load balancing on the electrical grid has become more challenging. One solution to this problem is controlling the load side instead of the production. For demand-side control, knowledge about the connected loads is required. Current smart plugs on the market lack the ability to detect the type of load connected. There are promising solutions published in the literature to the problem of identifying loads in a smart plug. These solutions, however, lack the ability to correctly detect if the connected load is not amongst the loads used during the training of the device. As most classification methods divide the entire feature space into the classes used in training, modifications are required to detect previously unseen electric devices. Accurate classification enables the precise control and scheduling of electric power loads. Misclassification of an unknown load can lead to problems in the system.

In our previous work [1] we have introduced SP4LC, a smart plug capable of identifying different types of household electric loads. In this paper, we use the previously collected data and show that it is possible to create a solution to detecting loads not seen previously. With such a solution, after detecting the unknown load, the smart plug can gather the data sufficient to detect the device in the future, as well as prompt the user to specify the device name and load profile. This ensures that load control and scheduling are not applied incorrectly to unknown devices.

The structure of the rest of the paper is as follows. Section II. summarizes the related work in literature. In Section III., the authors' previous work is summarized, introducing the dataset created by the authors and used for the classification. Section IV. introduces the definition and goal of open set recognition. The open set classification results are shown in Section V. Section VI. contains the conclusions.

II. Related Work

One of the goals of electrical load classification is to enable control of the demand-side, which is required with the introduction of non-controllable renewable resources in the electrical grid. This is essential to efficiently make use of renewable resources such as wind or solar power [2]. M. Jaradat et al. divide loads into two categories: must-run appliances and scheduled appliances. Their case used previous data about the appliance and power usage. For such a system to work correctly, identification of the loads is required.

Most solutions to the classification problem of electrical loads use power measurement data. A. Ridi et al. distinguish two main approaches [3]. Non-Intrusive Load Monitoring (NILM) is achieved typically by a single measuring device such as a smart meter placed at the meter panel. Intrusive Load Monitoring (ILM) can be achieved using smart plugs, measuring only a single electrical load per plug. The problem with NILM is that it measures only the total consumption and thus needs load power usage signatures and a method to decompose the total consumption into individual loads. The disaggregation method used in [3] relies on precise knowledge about power usage curves for each load. A solution to this is to measure each load individually and train the model on the acquired data (Manual-Setup ILM) or use Automatic-Setup ILM, which relies on previous knowledge about the characteristics of possible appliances [4]. The detection of a previously unseen load presents a crucial problem since disaggregation relies on load signatures.

In the ILM method, smart plugs currently on the market lack load identification capabilities [5]. It is possible to control the appliances with voice commands [6] using smart plugs, but the end-user has to assign which plug belongs to which appliance. Industry lags behind literature regarding smart plugs. Luis Gomes et al. present a system that uses shared knowledge and environmental sensors to determine useful information such as whether the appliance is being used or whether it will be used within the next hour [5]. This information can be used to schedule the running of the loads and turn off appliances that are not needed.

There are several methods presented in the literature using smart plugs to identify electrical loads. In [7], smart plugs were used to measure the Electric Load Signature (ELS) of five appliances. Decision tree and Naive Bayes algorithms were used to detect the five connected devices. This method lacks ways to detect if an unknown load is connected and would classify the load as one of the five appliances used during the training of the models. An interesting solution is presented in [8] which uses voltage-current trajectories to classify loads into seven categories. However, the model presented is only capable of classifying each load into one of the seven categories. A. Ridi et al. in [9] used time-series data recorded by smart plugs with K-Nearest Neighbor and Gaussian Mixture Models algorithms to classify ten different household electrical loads. The methods presented lack any detection capabilities for previously unseen loads.

In summary, the current cutting-edge solutions for electrical load recognition systems lack the ability to detect previously unseen devices and can only recognize loads known during training.

III. Previous Results

In the authors' previous work presented in [1], an active load classification system was introduced which uses the characteristic response of an electric load to the manipulation of its sinusoidal voltage curve to identify the load connected. Less than 10 seconds of measurement data is required to achieve above 99.5% accuracy.

A measurement prototype device was created that measures different voltage cutoff ratios for a given amount of AC periods. This method is shown in Fig. 1. The collected data is structured in matrices. One example of this is shown in Fig. 2.

Measurements were taken with different measurement profiles. The measurement profile defined the size of the measurement matrix by determining which cutoff ratios the prototype used and the number of AC periods measured. Information about measurement profiles used is available in Table I.

TABLE I
Measurement Profile Information

Measurement profile	Measurement time	Matrix size
TEST_ORIG	9.76s	14×20
TEST_HALVED	2.36s	7×10
TEST_TINY	0.56s	2×12
TEST_FOUR	0.88s	4×8

Twelve typical household electrical devices were measured. As this paper uses the same dataset as [1], we include the list of devices and labels used further in this paper:

- ipad10W - A 10W Apple USB adapter charging iPad
- usbapple5V1A - A 5W Apple USB adapter

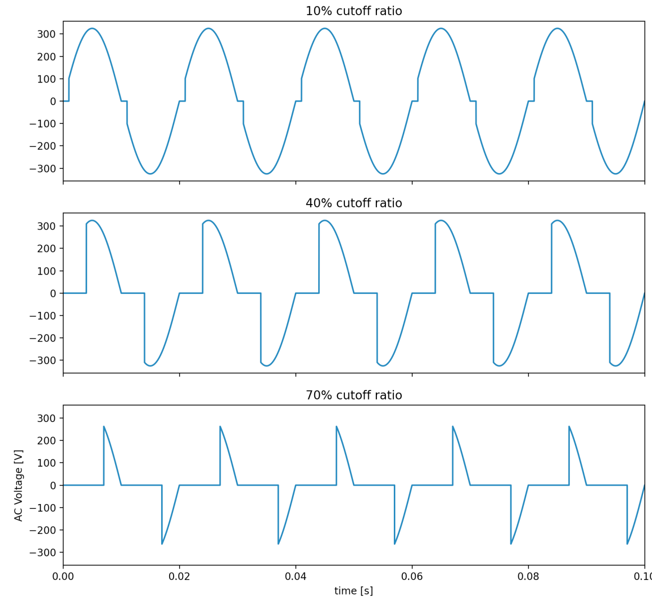

Fig. 1. Voltage cutoff method used in SP4LC with different cutoff ratios. The graphs show the AC voltage curves with different cutoff ratios. The cutoff starts are synchronized to the zero crossings.

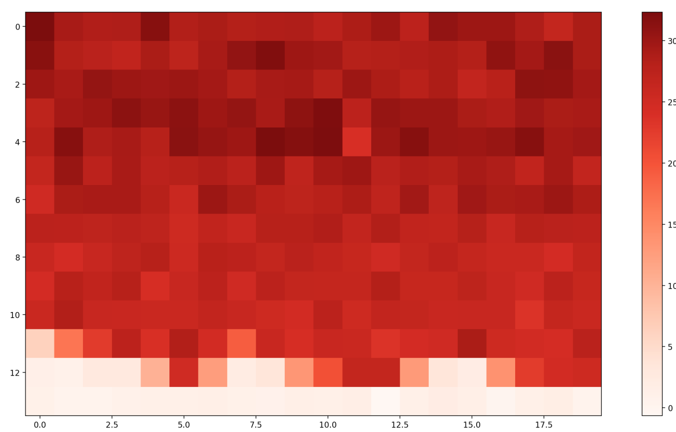

Fig. 2. Power measurement matrix of an LCD monitor. (Measurement unit: W)

- usb5V1A - A 5W generic USB adapter
- batterycharger4A - A four ampere ”smart” lead-acid battery charger
- batterycharger800mA - An 800mA traditional lead-acid battery charger
- fan - A fan
- hairdryer - A hairdryer
- incandescentbulb - An incandescent light bulb
- irlamp - An infrared heat lamp
- laptop - A laptop charger charging the laptop
- monitor - An LCD screen
- solderingiron - A soldering iron

The collected data were classified by different methods to enable the continuation of the research into both computationally resource-intensive and resource-constrained areas. Measurement profiles were also introduced to enable the reduction of data collection in edge computing solutions which also requires less computational resources during classification. Support Vector Machines (SVM), Fully Connected Neural Networks (FCNN), and Convolutional Neural Networks (CNN) were used. The classification average results are shown in Table II. With SVM and FCNN, ten statistics-based features were calculated from the measurement matrices which were used for the classification:

- The mean and standard deviation of the matrix elements.
- The mean and standard deviation of the standard deviations of matrix rows.
- The mean and standard deviation of the standard deviations of matrix columns.
- Mean of 2×2 submatrices on the 4 corners of the original matrix, divided by the mean of the entire matrix.

TABLE II
CLASSIFICATION RESULTS IN [1]

Classification method Sample size (train-test)	SVM 30 - 220	FCNN 100 - 150	CNN 150 - 100
TEST_ORIG	99.56%	99.51%	99.92%
TEST_HALVED	98.74%	98.52%	99.90%
TEST_TINY	97.40%	97.88%	-
TEST_FOUR	99.35%	98.50%	99.35%

IV. OPEN SET RECOGNITION

Traditional classification methods partition the entire feature space into regions, each corresponding to a specific class. However, in most cases, these methods cannot include every possible class and therefore falsely classify unknown inputs as one of the classes used during the creation of the model. Open set recognition presents a solution to this problem. W. J. Scheirer et al. formalize this problem in [10] as finding a recognition function f that minimizes the ideal risk $R_{\mathcal{I}}$:

$$\arg\min_{f}\left\{R_I(f) := \int_{\mathbb{R}^d\times\mathbb{N}} L(x,y,f(x))P(x,y)\right\} \quad (1)$$

Where d is the dimension of the feature vectors, y is the number of target classes ($y \in \mathbb{N}$) and $P(x,y)$ is the unknown probability distribution over $\mathbb{R}^d \times \mathbb{N}$. The aim is to find f which minimizes the loss function $L(x,y,f(x))$ ($L(x,y,f(x)) \geq 0$ and $L(x,y,y) = 0$). The difficulty of the problem is that $P(x,y)$ is unknown. To estimate $P(x,y)$ some prior knowledge is required about the probability distribution itself.

W. J. Scheirer et al. show that information about the location of known (positive) samples can be used to solve this problem. Intuitively, there is more risk involved in assigning a known label to those regions of the feature space which are located further from known data points.

Our approach follows the approach presented above to open set recognition. We used a one-class SVM classifier with a Radial Basis Function (RBF) kernel to achieve open set recognition. In all open set recognition tasks, the risk considerations have to be adjusted to the specific application. In a load classification system, we considered the following:

- The whole system makes decisions based on the types of loads connected. Load scheduling profiles are applied based on the class of the load.
- Load class data combined with previously recorded power trajectories can be used to estimate future grid load.
- If an unknown load is detected, the system requires external input. If the load is falsely classified as unknown, the correct class must be set. If it is a genuinely unknown class, the smart plug takes measurements, and the classification model is adjusted to recognize the device in the future.

V. CLASSIFICATION RESULTS

The task of load classification is to provide information about the load connected to the smart plug. The information can then be used to schedule or control the load. For these tasks, only the type or class of the load matters; distinguishing between different loads of the same class is not required. Since electric loads of the same function generally have similar electrical structures and components, distinguishing between them would also be challenging. We have demonstrated in [1], that our method cannot distinguish accurately between USB adapters of different brands. This means that there is a level of generalization involved in the measurement methodology, and new devices of the same class could be recognized correctly.

Since several decisions are taken by the system based on the class of load, we chose to optimize parameters of the classification model to minimize the misclassification of an unknown load as known. This means that the model should recognize truly unknown classes correctly at the cost of labeling some of the known inputs as unknown.

We used the dataset introduced in Section III. A one-class SVM classifier with an RBF kernel was used. As distinguishing between USB chargers is not part of the task of load classification, only one load class for USB devices was used (ipad10W). The input of the classifier was not the raw matrices but the extracted features introduced in Section III.

The methodology was the following. One class was selected as the unknown class, from which no samples were used during training. From the other classes, 150 out of the 250 samples available per class were used to train the one-class SVM model. The coefficient of the RBF kernel was set by taking into consideration the requirements described above. The one-class SVM classifier predicts whether a measurement is known or unknown. The classification of a known load can be achieved using the methods presented in [1].

The validation was run by classifying all measurement data with the trained one-class SVM model: the training samples, the samples of the known classes that were not used during training, and all the 250 samples from the unknown class. The results are shown in Fig. 3. The four tables show the classification results for each measurement profile. For each measurement profile, the classification was run for each of the

Test profile:	TEST_ORIG		
	Training	Test (known class)	Unknown class
Sample size:	1350	900	250
Omitted class	Classification accuracy		
ipad10W	97.41%	94.93%	100.00%
batterycharger4A	97.62%	95.46%	99.60%
batterycharger800mA	97.41%	95.05%	100.00%
fan	97.31%	94.96%	99.99%
hairdryer	98.36%	96.85%	100.00%
incandescentbulb	97.31%	94.78%	83.60%
irlamp	97.33%	94.84%	100.00%
laptop	97.85%	95.90%	100.00%
monitor	97.41%	94.87%	98.64%
solderingiron	97.45%	95.14%	100.00%
average accuracy	97.55%	95.28%	98.18%

Test profile:	TEST_HALVED		
	Training	Test (known class)	Unknown class
Sample size:	1350	900	250
Omitted class	Classification accuracy		
ipad10W	96.23%	92.76%	100.00%
batterycharger4A	96.48%	93.34%	100.00%
batterycharger800mA	96.27%	92.59%	100.00%
fan	96.14%	92.58%	91.53%
hairdryer	98.10%	96.33%	100.00%
incandescentbulb	96.18%	92.78%	11.16%
irlamp	96.26%	92.64%	98.49%
laptop	96.82%	93.90%	100.00%
monitor	96.19%	92.56%	96.18%
solderingiron	96.22%	92.72%	100.00%
average accuracy	96.49%	93.22%	89.74%

Test profile:	TEST_TINY		
	Training	Test (known class)	Unknown class
Sample size:	1350	900	250
Omitted class	Classification accuracy		
ipad10W	96.94%	94.09%	100.00%
batterycharger4A	97.76%	95.75%	100.00%
batterycharger800mA	96.92%	94.14%	100.00%
fan	96.86%	94.23%	100.00%
hairdryer	97.74%	95.64%	100.00%
incandescentbulb	96.89%	93.97%	63.52%
irlamp	96.90%	94.03%	90.12%
laptop	97.23%	94.36%	98.33%
monitor	96.99%	94.35%	100.00%
solderingiron	96.83%	93.75%	42.76%
average accuracy	97.11%	94.43%	89.47%

Test profile:	TEST_FOUR		
	Training	Test (known class)	Unknown class
Sample size:	1350	900	250
Omitted class	Classification accuracy		
ipad10W	95.15%	90.66%	100.00%
batterycharger4A	95.69%	91.77%	99.98%
batterycharger800mA	95.14%	90.52%	100.00%
fan	95.09%	90.62%	83.03%
hairdryer	97.83%	95.93%	100.00%
incandescentbulb	95.15%	90.51%	0.62%
irlamp	95.13%	90.56%	96.26%
laptop	95.74%	91.78%	100.00%
monitor	95.22%	90.79%	97.03%
solderingiron	95.18%	90.57%	100.00%
average accuracy	95.53%	91.37%	87.69%

Fig. 3. SVM-based Open Set classification results (average of 100 runs).

ten classes as the unknown class. The training column shows the percentage of the training data (1350 in total, 150 samples form each class except the unknown class) correctly classified as known. The test column shows the percentage of correctly identifying the samples of the known classes as known (900 in total, 100 samples per known class, these samples were not used during the training of the model). The last column shows the percentage of the 250 samples from the unknown class correctly classified as unknown.

It is essential to consider that the goal is to minimize incorrectly classifying an unknown load as known. It is acceptable that some of the known samples are classified as unknown. The results in Fig. 3 show that the measurement profiles containing more data achieve better accuracy. Another interesting observation is that the incandescent light bulb performed the worst in terms of correct identification as unknown. One reason can be that, in fact, the infrared heat lamp (irlamp) also uses an incandescent bulb emitting infrared radiation. Similar behavior was observed in [1] using CNN classification, where the model could not distinguish the two classes. It indicated that the generalization capabilities of the model worked correctly.

VI. Conclusions

This paper has presented a solution to detecting previously unseen electrical loads using a smart plug. The results show that with less than 10 seconds of measurement data, an unknown load can be detected with 98.18% accuracy, while known electrical loads can be correctly identified as known with over 95% accuracy. Combined with the methods presented in [1], an automated smart plug system can be built which can both identify and control electrical loads. With open set recognition capabilities, the smart plug can initiate the measurement data collection if an unknown device is detected. With the data collected, the load can be identified in the future. The only manual input required would be the class name and load schedule information. With each measurement taking less than 10 seconds, fast identification of loads is possible, and profiling an unknown load takes significantly less time than in the case of time-series recognition methods.

A. Future Work

In this paper, we have used an SVM-based open set recognition, but there are other methods in literature such as PI-SVM or EVM. We intend to examine the performance of other types of open-set recognition methods. SVM requires fewer resources compared to other solutions such as Neural Network-based ones. This allows the model to run fast even in resource-constrained environments such as in Edge Computing solutions. This is another area considered for future research. The microcontroller used in the smart plug is the WiFi-capable ESP32. There may be classification methods such as SVM, which could be run on the microcontroller. With the WiFi capabilities of the smart plug, a Wireless Sensor Network could be built. Moving the entire classification process or parts of it to the microcontroller allows the smart plug to make decisions locally and also reduces the bandwidth used by the device.

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