PLUG LOAD IDENTIFICATION IN EDUCATIONAL BUILDINGS USING MACHINE LEARNING ALGORITHMS

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ABSTRACT

Plug loads accounts for 20% to 30% of building energy consumption and has an increasing trend. Automatic plug load identification is one of the technique for effectively managing the plug load consumption. There are several studies on Non Intrusive load monitoring (NILM) but limited studies on Intrusive load monitoring (ILM). ILM is a technique that uses a low end power meter on every plug load to monitor it's power consumption. In this paper, machine-learning techniques are applied on low-frequency ILM data for identification of plug load and it's state (ON/Sleep). The results show the identification accuracies are close to 98%.

INTRODUCTION

Reducing energy demand reduces CO_2 emissions. Evidence shows that energy feedback information provided by smart meters can enable consumers to reduce consumption between 5% to 15% (Darby, 2006) and that appliance-specific consumption information is more useful than aggregate information (Fischer, 2008). It is reported that plug loads currently consume more electricity than any other single end-use service in residential buildings. In commercial buildings plug loads consume around 20% to 30% of building energy and its consumption is rapidly growing (Ghatikar et al., 2014).

Plug strips can be a good solution for controlling plug load consumption. A smart strip can function effectively if it has plugged in load identification capability. The benefits of a smart plug strip (Ridi et al., 2014) are:

1. More detailed power consumption data available to monitor the plug loads
2. Effective plug load management to achieve energy efficiency and user comfort
3. Remote monitoring and control of devices
4. Reduction of standby loads
5. Detection of faulty devices
6. Human activity prediction
7. Finer load prediction possible
8. Demand response management

Plug loads are very diverse in nature and of different makes, types, and brands and therefore to identify a plug load is challenging. There are two different approaches for device identification. The first approach is NILM that uses single point sensing to collect load data of the whole building and then applies load disaggregation techniques to identify the loads connected in the building (Hart, 1992). The identification problem is usually formulated as an optimization problem that finds the best matching pattern similar to the measured load. In NILM, the complexity increases as the number of devices increase. Smaller loads, variable loads, and identical loads may not be identified properly. The main advantage of NILM is that it is more economical. The second approach is ILM, where the plug load data is collected by power meters at the plug level. The unique consumption pattern of a device is called the load signature. Different machine learning techniques are applied on these load signatures for identifying the load. The learning algorithms use historical data and build device identification model. In ILM, it is also possible to control the attached device. The reducing cost of electronic meters is making intrusive load monitoring a good option.

A brief review of works done in ILM is presented here. A good survey on ILM for appliance recognition can be found in (Ridi et al., 2014). In a work by (Zufferey et al., 2012), a plug based low end sensor called PLOGGs has been used to measure energy consumption at low frequency typical one sample every 10 Seconds. They have applied Gaussian Mixture Model (GMM) and K-Nearest Neighbor (KNN) and got 85% accuracy results for identification.

In (Reinhardt et al., 2012a), the authors use distributed high resolution current sensors to capture the energy consumption data of devices at a high sampling rate of 1.6 kHz. In a period of 320 ms, 512 current readings were recorded. For a range of household appliances, 3,000 such current consumption fingerprints were captured. A total of six devices of five different types were included in the study. Steady state features gave 80% accuracy using Bayesian Network Classifier. Inrush current feature gave 99.3% accuracy and using both inrush and steady state features gave them 100% accuracy. Also authors showed that including harmonics along with other features increased the accuracy. The authors have compared the accuracy of different classification algorithms and also the time taken to build the model. Transient and steady state features such as IRMS, IAVG, Phase shift, magnitudes of the fundamental frequency and the first four odd harmonics (i.e., 150 Hz through 450 Hz for a mains frequency of 50 Hz) and magnitude of DC offset were used in identification. Accuracy of 98% was reported.

In another work by (Reinhardt et al., 2012b), distributed load metering was used to capture 1000 power consumption traces from 31 different types of appliances during the 24 hours of a day. A repository of more than 100 devices called Tracebase was created. They extracted various time dependent features and

other statistical features such as maximum power, average, and median power during different times of the day. They used random committee algorithm for identifying the devices with an accuracy of 95%.
(Ridi et al., 2013) have created ACS-F1 (Appliance Consumption Signature Fribourg-1) dataset containing 1 hour data for each of the 100 devices in 10 device types. The data was collected at a frequency of 1 sample every 10 seconds. The features such as P, Q, IRMS, VRMS, Frequency, and Phase angle were used. The data pre-processing like Normalization, Delta coefficients and Delta-Delta coefficients features were applied to improve the quality of features. Standard learning methods like GMM and K-NN algorithm were used for identifying the devices. They claimed an accuracy of 93% on their dataset.
A distributed high-frequency measurement of electrical voltage and current for device identification was proposed by (Englert et al., 2013). Supervised machine learning algorithm such as Random Forest was applied to identify device type as well as its operation mode. The feature vector contained Active Power, Phase difference, Crest factor, RMS current and first 50 Harmonics. A dataset of 40 devices in different operating modes were used. They reported an accuracy of up to 99.8%. The data acquisition needs a specialized power meter to record data at high frequency.
The work presented here differs from the earlier methods in various aspects such as dataset creation, selection of appropriate sampling frequency and duration of sampling, study of plug loads for only academic buildings, inclusion of device state information, selection of relevant features for identification etc. A dataset of 9 different types of plug loads containing 10 devices in every type were collected. Devices included within each type are not identical. The data also includes device state information. Relevant features were identified from a set of features and used for identification. A low resolution data was collected with a sampling rate of one reading taken every 2 seconds for a duration of 2 minutes. It was observed that this data was sufficient to identify the device type, device, and its state or operating mode with a very high accuracy. Some of the earlier works either have used very high data sampling frequency which increases the cost of data acquisition or use very low data sampling frequency which make them less accurate and also require more time for device identification.

DEVICE IDENTIFICATION APPROACH

Data classifiers are widely used in automated applications because of its ability to learn from the observed data. Given a set of training data points along with associated class labels, a classifier determines the class label for an unlabeled test instance. Data classification algorithms are used for device identification. In the first step or training phase, the classification algorithm to build a model analyzes the training data set consisting of power consumption signature of the devices. In the second step or testing phase, the classifier predicts or recognize unseen device based on the learned model. The overall work-flow of the device identification process is shown in Figure 1.
The accuracy of the classifier is the number of correctly identified devices in testing phase. The model building can take place in a centralized system or within a smart strip. In the centralized system approach, there is a possibility of single point failure and also there is an overhead of communication between smart strip and centralized system. The advantage of centralized system is it can run complex identification tasks easily. In some smart plug strips, the device identification task is performed internally. For this type of smart plug strip, a memory efficient and light weight machine learning algorithm is suitable.

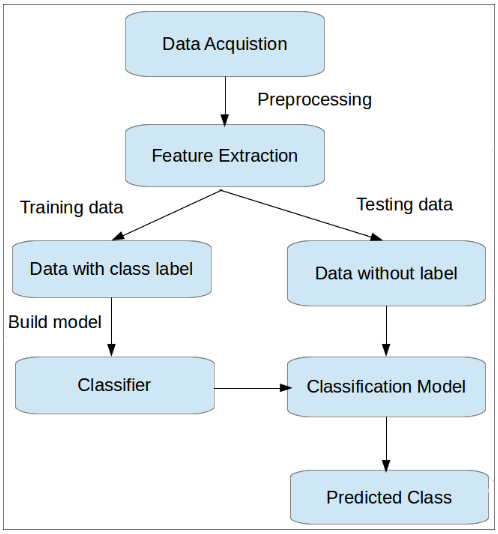

Figure 1: The plug load identification process

Data Acquisition

This section explains the data collection process which is one of the major tasks as it influences the results and findings of the study. A dataset of the power consumption signatures of the plug loads was created. There are numerous plug loads and creating a very generic plug load identification solution was avoided. The plug loads that are commonly found in an educational buildings have been included. A standard power meter was used to record the data.
The power consumption signatures of 90 plug loads from 9 different device types were collected. The device types were CPU, Printer, Monitor, Laptop, Mobile, Network switch, Kettle, Projector, and Televisions. In each device type, 10 plug loads of different make and brands were chosen to effectively represent the characteristics of that particular device type. The data was collected at a sampling rate of one reading taken every 2 seconds. The plug load data was collected for 2 minutes in different states such as sleep state or ON state. OFF state of the device was not included because for most of the devices, consumption

pattern is nearly zero. To capture the variation in the pattern of energy consumption for laptop, the data was measured in both full discharge mode and full charged mode. Similarly, for monitors the data of full brightness and medium brightness of monitor was collected. The total number of samples in the database was 9000. Every data sample has 41 different features. The feature set includes instantaneous voltage, RMS voltage (VRMS), RMS current (IRMS), active power (P), reactive power (Q), apparent power (S), power factor (PF), phase angle (Phi), frequency, peak voltage (Vpeak), peak current (Ipeak), first 10 current harmonics, first 10 voltage harmonics, and first 10 power harmonics. The dataset is publicly available for download at https://github.com/Raghuna/plugload-data. The list of plug loads included in the dataset is shown in Table 6.

Feature Extraction

After data acquisition, the next step was to do feature selection or feature extraction. The data was preprocessed and appended with the class labels for performing the identification task. After adding the class labels, feature selection techniques were applied to choose appropriate features from the set of features. Initially, data with all 41 features was selected without checking the relevance of these features for identification.
Feature or attribute selection is the process of selecting a subset of relevant features for use in model construction. Feature selection can significantly improve the comprehensibility of the classifier models and often build a model that generalizes better on the unseen data and avoids over fitting. Feature selection helps in improving the quality of data which helps in speeding up learning algorithm. Having more features usually means the need of more instances resulting in complex model. According to *Occam's Razor*, developed by William of Occam, a complex classifier tends to be less accurate compared to a simpler classifier. Various types of feature selection methods (Tang et al., 2014) available in Weka data mining tool such as *Chi-squared Ranking Filter, InfoGainAttributeEval, Gain Ratio feature evaluator* and *OneR* feature evaluator were applied (Hall et al., 2009). A set of common relevant features were extracted. The features like VRMS, IRMS, PF, Phi, P, Q, S, Vpeak, and Ipeak were shown to be useful. Frequency turned out to be a redundant feature as it has the same value for all devices. Also, the odd harmonics of voltage, current, and power were also ranked lowest terming them as irrelevant. This was obvious as the odd harmonics values are not prominently expressed as compared to even harmonics.

Device Identification Task

The identification task was divided into three separate tasks. The class labels were assigned based on identification task.

1. Identification of individual devices such as Lenovo laptop, Nokia Lumia mobile, HP laser Jet 3055 printer, Smart style eco pc etc. The class labels for this task are the device numbers from 1 to 90 uniquely assigned to each device.
2. Identification of device types such as CPU, Laptop, Printer, Mobile, Monitor etc. The class labels for this task are the device types and ranges from 1 to 9.
3. Identification of device state and its state such as "CPU ON", "Monitor Sleep" etc. The class label assignment for this task is shown in Table .

Table 1: Class label assignment table

Device Type	Device State	Class Label
CPU	Sleep	1
CPU	ON	2
Laptop	Sleep	3
Laptop	ON	4
Monitor	Sleep	5
Monitor	ON	6
Printer	Standby	7
Printer	print/scan	8
Kettle	ON	9
Mobile	Charging	10
Network switch	ON	11
Projector	Standby	12
Projector	ON	13
Television	Standby	14
Television	ON	15

RESULTS

The classifier performance was tested in two ways:

1. **Hold Out method**: The dataset is randomly split into two sets, one set used for training, the other as testing. Here the training data is used to build the classifier model and the test set data is used for measuring the performance or accuracy of the classifier.
2. **K-fold Cross-Validation**: In K-fold cross-validation method, the data is randomly portioned into k sets. In every experiment, one set is treated as test set and the remaining k-1 sets are used for training. The average of the experiment is the final accuracy.

The accuracy of a classifier on a given test set is the percentage of test set tuples that are correctly classified by the classifier. All the values given in the tables are in percentages. The results show that the accuracy of device identification is less dependent on the harmonic features. A classifier with simple features such as VRMS, IRMS, PF, Phi, P, Q, S, Vpeak, and Ipeak will be able to identify the device almost with the similar accuracy. Simple power meter data which can provide some basic electrical features with low frequency can be used for device identification. One of the main advantages of high frequency data is that instant device identification is possible. The identification takes

Table 2: Device Identification using all 41 features

Algorithm	Device Type		Device		Device State	
	Split (70/30)	5-fold CV	Split (70/30)	5-fold CV	Split (70/30)	5-fold CV
KNN	98	99	95	96	98	98
SVM	97	98	96	95	96	97
NB	59	52	82	83	52	53
LR	81	81	94	94	82	84
RF	99	100	99	100	99	100

Table 3: Device Identification using Irms, Vrms, P, Q, S, Phi, PF, Ipeak and Vpeak features

Algorithm	Device Type		Device		Device State	
	Split (70/30)	5-fold CV	Split (70/30)	5-fold CV	Split (70/30)	5-fold CV
KNN	98	99	95	96	98	98
SVM	96	97	93	95	96	97
NB	45	44	59	59	48	49
LR	52	54	60	61	57	57
RF	99	99	97	98	98	99

2 minutes for the low frequency data used in this study. In this study, Scikitlearn machine learning package was used (Pedregosa et al., 2011). Various machine learning classification algorithms such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Naive Bayes (NB), Logistic Regression (LR), and Random Forest (RF) were applied and compared. The results of the device classification using all 41 features are shown in Table 2 and the results of the device classification by using only features such as VRMS, IRMS, PF, Phi, P, Q, S, Vpeak, and Ipeak are shown in Table 3. The KNN, SVM and RF classifier perform quite well as shown in the tables 2 and 3.

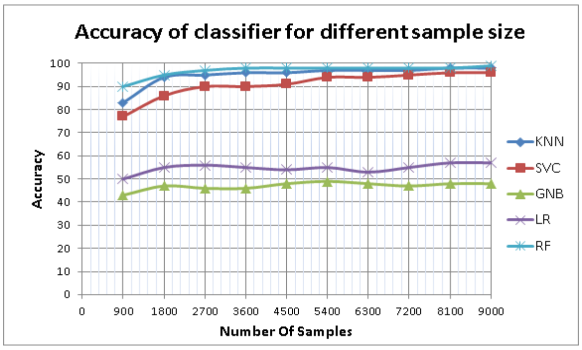

Figure 2: Accuracy v/s sample size

The graphs in Figure 2 shows how the accuracy of classifier varies with the sample size (10% to 100%). The data set was prepared by sampling the required percentage of data from the original data of 9000 samples. The data includes only relevant features. Figure 2 shows that with about 20% of the data (1800 samples or equivalently recording 1 sample for every 10 seconds), the classifiers such as KNN, and SVM will properly identify plug loads and its operating state with good accuracy.

More detailed results of identification of device state using SVM is shown by a confusion matrix in Table 4. The training set contains 70% (6300) and test set contains 30% (2700) samples. Entry i,j in a confusion matrix is the number of observations actually in group i, but predicted to be in group j. The diagonal elements represent the number of points for which the predicted label is equal to the true label, while off-diagonal elements are those that are mislabeled by the classifier. The higher the diagonal values of the confusion matrix, the better the indication of obtaining correct predictions.

Table 4: Confusion Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	200	1	0	0	0	0	0	0	0	0	0	1	0	0	0
2	1	170	1	5	0	0	0	0	0	0	0	0	0	0	1
3	0	0	179	4	0	0	0	0	0	0	0	0	0	0	0
4	0	0	1	168	0	3	0	1	0	0	0	0	0	0	0
5	0	0	0	1	188	0	0	0	0	0	0	0	0	0	0
6	0	0	0	2	0	181	0	0	0	0	0	0	0	0	0
7	1	0	0	0	1	0	187	0	0	0	0	0	0	0	0
8	0	0	1	33	0	0	0	129	0	0	0	0	0	0	0
9	0	0	0	4	0	0	0	0	188	0	0	0	0	0	0
10	0	0	0	1	0	0	0	0	0	174	0	0	0	0	0
11	0	0	0	3	0	0	0	0	0	0	181	0	0	0	0
12	0	0	0	3	0	0	0	1	0	0	0	150	0	0	0
13	0	0	0	20	0	0	0	0	0	0	0	0	148	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	174	0
15	0	0	0	5	0	0	0	1	0	0	0	0	0	0	187

- True positive (TP): It is the value in diagonal position
- False positive (FP): It is the sum of column x (excluding the main diagonal)
- False negative (FN): It is the sum of row x (excluding the main diagonal)
- True negative (TN): It is the sum of columns and rows (excluding that class's column and row)

Precision: The number of correctly classified positive examples divided by the number of examples labeled by the system as positive

$$Precision = \frac{TP}{TP + FP}$$

Recall: The number of correctly classified positive examples divided by the number of positive examples in the data

$$Recall = \frac{TP}{TP + FN}$$

F1 Score: The F measure is the harmonic mean of precision and recall.

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall}$$

Support: The support is the number of samples of each class.
The classification report is shown in Table . Precision, recall and F1-score are nearly 1, which implies that the classifier was able to properly identify the device and its operating state.

Table 5: Classification report

	Precision	Recall	F1-Score	Support
1	0.99	0.99	0.99	202
2	0.99	0.96	0.97	178
3	0.98	0.98	0.98	183
4	0.67	0.97	0.8	173
5	0.99	0.99	0.99	189
6	0.98	0.99	0.99	183
7	1	0.99	0.99	189
8	0.98	0.79	0.87	163
9	1	0.98	0.99	192
10	1	0.99	1	175
11	1	0.98	0.99	184
12	0.99	0.97	0.98	154
13	1	0.88	0.94	168
14	1	1	1	174
15	0.99	0.97	0.98	193
avg/total	0.97	0.96	0.97	2700

DISCUSSION

KNN algorithm was tested on the smart strip that was developed in-house in this work. The smart strip was used for collecting data and the computer for identifying the device. The smart strip records the signature of plug loads and communicates it over ZigBee to a centralized computer. There is a request and response type of communication between the smart strip and the computer. The computer was able to remotely identify the connected load.
Some of the limitations of the study need to be addressed. The dataset is not generic and does not exhaustively contain all the plug loads used in educational buildings. The variations in the load signatures of plug loads under different sources of supply like UPS, diesel generators etc. have not been considered. The variation in load signatures would effect the accuracy of device identification. The classifier has to be embedded on the smart strip for controlling the plug load.

CONCLUSION

A low frequency dataset of nine different types of plug loads each with ten devices was created. The dataset contains the plug loads that are commonly used in academic premises. The dataset has a wide variety of devices in each type and very few such datasets are available for practical evaluation. Plug load identification using different machine learning algorithms were tested on this dataset. The study shows that simple algorithms like KNN yields good accuracy in identifying the device and that a low frequency data of 2 minutes gives good accuracy. The sampling rate can be as low as one sample every 10 seconds. It was seen that accuracy of identification is not dependent on harmonic features and also frequency. Low cost distributed energy metering sensors would be sufficient for plug load and operating state identification.

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Table 6: List of plug loads in dataset

Device-id	Device type	Device	Device-id	Device type	Device
1	CPU	Zenith h67m	46	Kettle	Phillips big
2	CPU	Cooler master	47	Kettle	Phillips small
3	CPU	HP compaq	48	Kettle	Pigeon
4	CPU	Dell t3600	49	Kettle	Prestige big
5	CPU	Beetel	50	Kettle	Prestige small
6	CPU	HCL AMD	51	Mobile	Assus
7	CPU	HCL AMD athlon	52	Mobile	HTC
8	CPU	Integration Eco pc	53	Mobile	HTC desire
9	CPU	Think center	54	Mobile	Moto e
10	CPU	Zenith cv	55	Mobile	Nexus 4
11	Laptop	Assus 5vu58e-1a	56	Mobile	Samsung duosstar
12	Laptop	Dell 1440	57	Mobile	Nokia lumia
13	Laptop	Dell 5537	58	Mobile	Samsung duos
14	Laptop	Dell 4010	59	Mobile	Sony experia
15	Laptop	Dell i53550	60	Mobile	Samsung young
16	Laptop	HP 444	61	N/w Switch	Cisco aeronaut1240
17	Laptop	Lenovo g580	62	N/w Switch	Linksys
18	Laptop	Lenovo e430	63	N/w Switch	Catalyst 2950
19	Laptop	Lenovo e5430	64	N/w Switch	Catalyst 2960
20	Laptop	Sony VAIO	65	N/w Switch	Compex tp1016c
21	Monitor	Zenith 18.5	66	N/w Switch	HP A3100
22	Monitor	Dell small	67	N/w Switch	HP h3cs5120
23	Monitor	Dell large	68	N/w Switch	Juniper ex200
24	Monitor	Dell 2240	69	N/w Switch	Linksys slm224g2
25	Monitor	Dell touch	70	N/w Switch	Belkin N750
26	Monitor	Flatron	71	Projector	NEC vt480
27	Monitor	HCL hcm	72	Projector	Epson
28	Monitor	HP crt	73	Projector	Epson emp55
29	Monitor	HP l1706	74	Projector	Hitachi cpx3030
30	Monitor	Think vision	75	Projector	Hitachi
31	Printer	HP 3055	76	Projector	LG
32	Printer	HP 400m401	77	Projector	NEC lt280
33	Printer	HP clj2605	78	Projector	Panasonic00
34	Printer	HP lj1020	79	Projector	Panasonic ptbxo00
35	Printer	HP ljm2727	80	Projector	Sanyo 101h
36	Printer	HP lj400	81	Television	Akai
37	Printer	HP lj3015	82	Television	BPL
38	Printer	HP ojk7108	83	Television	LG flatron
39	Printer	Samsung 2160	84	Television	LG plasma
40	Printer	Scanner 3110	85	Television	Sony
41	Kettle	Bajaj platina	86	Television	Samsung easyview
42	Kettle	Phillip sf	87	Television	Samsung l4
43	Kettle	Morphy	88	Television	Samsung plano
44	Kettle	Morphy psrc	89	Television	Toshiba
45	Kettle	Optima	90	Television	Videocon