# Real-time Appliance Identification using Smart Plugs

Demo Abstract


Muhammad Aftab
Masdar Institute of Science and Technology
muhaftab@masdar.ac.ae

Chi-Kin Chau
Masdar Institute of Science and Technology
ckchau@masdar.ac.ae

Majid Khonji
Masdar Institute of Science and Technology
mkhonji@masdar.ac.ae



## Abstract

Automatic classification of electric appliances has many applications such as automated demand response, human activity observation, and energy analysis. We present a smart plug platform that supports real-time classification of consumption profiles of appliances in addition to remote control and consumption monitoring. Our platform is based on low-cost Arduino hardware platform. The smart plug offers RESTful web service which can be used to communicate with smart phones and web clients. Our smart plug platform has the capability to support additional features, such as big data analysis and detection of anomalous appliance behavior.



***CCS Concepts*** • **Computer systems organization → Embedded hardware**; **Embedded software**; • **Hardware** → *Sensor devices and platforms*;

***Keywords*** Smart Plug; Internet of Things; Appliance Identification

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## 1 Introduction

Buildings constitute a large portion of the overall energy consumption, nearly half of which is consumed by residential buildings [4]. To reduce the energy consumption of residential buildings and homes, it is necessary to know the types of electrical appliances in a home and their power consumption behavior. Every electrical appliance possesses its own power signature which can be used to automatically identify the specific appliance. In this research, we develop a smart plug platform that achieves the following goals: (i) accurate measurement the power consumption data of electric appliances, (ii) analyzing the collected data for real-time classification of the appliance energy consumption model, and (iii) remote control of the attached appliance. Our platform, which builds upon our previous work [1], is based on the popular and cheap Arduino hardware platform. The smart plug offers RESTful web APIs which can be utilized by smart phones and web clients to interact with the smart plug. In particular, the automatic appliance identification feature of our smart plug platform offers many benefits to researchers, e.g., automated demand response, appliance localization, indirect monitoring of the occupant activities, and energy analytics.

## 2 Comparisons to Related Work

Electric signatures based appliance identification can be achieved using either non-intrusive methods or intrusive methods. Non-intrusive methods involve measuring the energy consumption of the entire house and disaggregating it to identify individual appliances. Intrusive methods require measuring the energy consumption of individual appliances in a home using some kind of energy meters or smart plugs. With a few exceptions [2], most of the proposed non-intrusive as well as intrusive methods do not perform real-time identification and instead work with pre-recorded data in an offline manner. Our smart plug system, on the other hand, supports real-time classification of the appliance energy consumption profile. In addition, it offers basic features such as appliance *On/Off* control and measurement of its energy consumption.

## 3 Implementation

First we describe the details of smart plug hardware and implementation, followed by our appliance identification approach.

### 3.1 Hardware

The Arduino-based smart plug contains sensors to measure the instantaneous AC voltage and current of the attached appliance. AC voltage is measured using 220V–9V step-down voltage transformer. AC current is measured using Hall Effect-Based Linear Current Sensor (ACS712). Knowing the instantaneous voltage and current, a variety of quantities can be computed, such as active power, reactive power, apparent power, root-mean-square voltage, root-mean-square current, power factor, and other power quality parameters. These quantities give a more accurate estimation of energy consumption which can be helpful in power quality monitoring, detection of malfunctions, etc.

The smart plug has a relay to control the power to the attached appliance, a micro SD card for data storage and big data analysis, and a WiFi module for radio communication. We use *ESP8266* WiFi module, which offloads all WiFi networking functions from the main Arduino (i.e., Arduino Pro Mini), enabling the main Arduino to utilize all resources for running the appliance identification algorithm. The WiFi module provides RESTful APIs for controlling the attached appliance and querying its status. The APIs can be accessed by basic HTTP commands from smartphones and web clients. Figure 1 shows the hardware components of the smart plug.

We develop an internet-connected base station based on Raspberry Pi, which supports WiFi connections to the smart plugs. The smart plugs transmits appliance power consumption data at periodic intervals to the base station. The base station provides APIs



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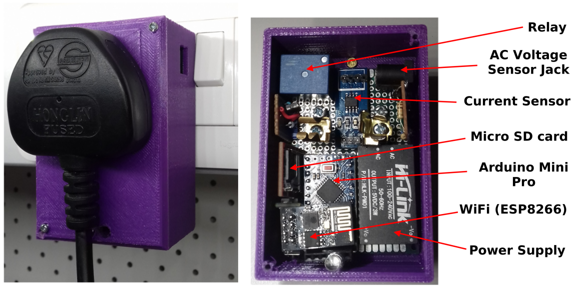


**Figure 1.** Hardware components of the smart plug.

which can be accessed by smartphones and web clients to visualize historical energy consumption data. The base station also provides remote access to the smart plugs for monitoring and control of appliances over internet. The high-level architecture of smart plug system is illustrated in Figure 2.

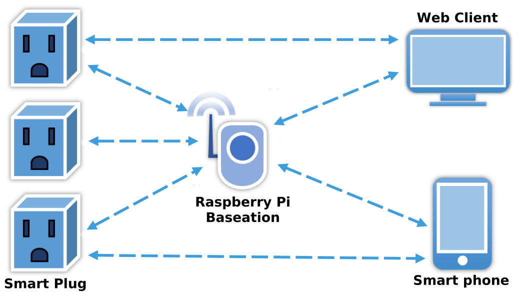


**Figure 2.** High-level architecture of the smart plug system.

### 3.2 Appliance Identification

Given the appliance power consumption data obtained at a sampling rate of 1Hz, the smart plug aims to infer the appliance energy consumption model. There are a few basic models suitable for describing the power consumption of appliances [4]:

1. *On-off model:* Appliances belonging to this model draw fixed power $P_{on}$ when active.
2. *On-off decay model:* In this case the appliance power consumption follows an exponential decay curve, dropping from initial surge power $P_{peak}$ to a stable power $P_{active}$ at a decay rate $\lambda$.
3. *On-off growth model:* The power consumption of these appliances follows a logarithmic growth curve, starting with a power level $P_{base}$ and a growth rate $\lambda$ .
4. *Stable min-max model:* These appliances draw stable power $P_{stable}$ with random upward or downward spikes $P_{spike}$. The magnitude of random spikes is uniformly distributed between $P_{stable}$ and $P_{spike}$. The interarrival time of spikes follow exponential distribution with mean $\lambda$.
5. *Random range model:* The power consumption of these appliances is similar to a random walk between a maximum power $P_{max}$ and a minimum power $P_{min}$, where the power consumption randomly varies within these bounds.
6. *Cyclic model:* These appliances exhibit repeating power consumption patterns.

Common resistive and inductive appliances exhibit on-off, on-off decay, or on-off growth behavior, whereas appliances with non-linear power consumption exhibit stable-min, stable-max, or random-walk behavior.

The smart plug analyzes the power consumption data to classify the appliance as belonging to one of the above models. For a given appliance, the smart plug chooses the model that best explains the observed power consumption. For the first three models, the smart plug uses linear least squares method to to fit a straight line, an exponential decay curve, or a logarithmic growth curve onto the data following a simplified version of the appliance identification algorithm proposed in [4]. To fit exponential curve, we employ a special technique proposed in [5], since fitting an exponential decay curve involves inferring three parameters (i.e. $P_{peak}$, $P_{active}$, $\lambda$), which can not be accomplished using the traditional linear least squares method. For the remaining three models, which are exhibited by appliances with non-linear power consumption, the smart plug fits a probability distribution. Figure 3 provides the preliminary results of appliance identification using our smart plugs for four different appliances. For each appliance, the identified model along with the model parameters are shown. We observe that our smart plugs are able to identify the true model for both linear and non-linear appliances.

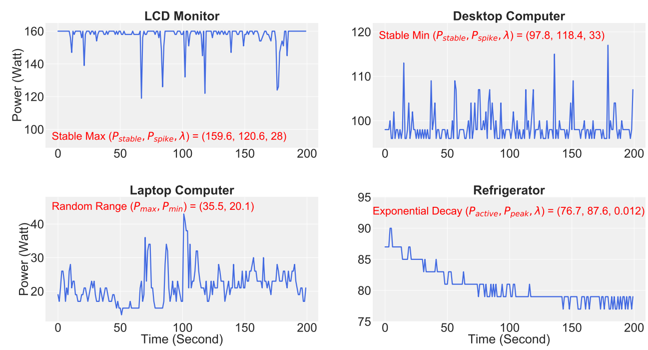


**Figure 3.** Appliance identification results.

## 4 Conclusion

This work presents a smart plug platform that can perform real-time appliance identification, offering several benefits to researchers and developers, e.g., demand response, appliance localization, human activity monitoring, and energy analytics, etc. The system consists of smart plugs based on Arduino open hardware platform. The system supports real-time appliance identification, appliance energy consumption monitoring, and remote control. Our smart plug platform can be extended to support additional features, such as big data analysis, detection of anomalous appliance behavior, and effective power allocation [3, 6].

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