博 士 論 文

Leveraging Smart Plugs with Machine Learning in Residential Power Managements
（住宅用電力管理向け機械学習型スマートプラグに関する研究）

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Abstract

To achieve the next generation of electric grid, commonly referred to as the Smart grid, several technologies new need to be created and refined to as to be able to handle increased renewable penetration, optimization of billions of consumption devices and the challenges on the informationization age. The electric grid is one of the last large infrastructure elements to undergo the informatization process as a means to reduce waste and improve performance. Several goals have been defined, which are designed to transition the electric grid of today into the smart grid which include: increased penetration of renewable energy sources, reduction in transmission losses and improvement of resilience and reliability by transitioning into more decentralised and small distribution networks such as microgrids and forms of demand side management to equally focus on the consumption side as much as the production and transport ones. This work focuses and the last of the three aspects by looking at way that electric consumption can be optimised in an effort to reduce electrical waste, peak demand and optimise the way electrical power is used across the network.

When considering demand side management, we must first preface it with the fact that this is a type of control mechanism used in situations where the electrical production has problems matching the consumption. While this may not be the case in may situation around the world, increased renewable penetration is the leading cause which drives the need from demand side management. Electrical energy coming from solar panels, wind turbines alongside other sources such as reverse hydro power, burnable methane, thermal and such, unfortunately are not as stable in the production as a nuclear power plant would be. This created fluctuates in time making production unstable due to a lack of inertia that keeps driving the system forward even in time of lower production. As a way to compensate for this we also look into way to create a simple and easy demand side management system which could be implementable both as a way to retrofit old buildings and be used in the next generation smart buildings. To achieve this we break the problem into two sections: 1) Real-time classification of electric loads, 2) Occupancy monitoring in indoor spaces.

(1) To be able to reduce electrical consumption, or perform any other type of optimization, we first need a way to accurately be able to identify and classify each and every type of electrical appliance connected to a consent or the local low voltage electrical line. One identified, the devices also have to be controllable in some way of fashion. A novel smartplug based approach is used, where we modify conventional smart plug designs with a small electrical element, a TRIAC, and perform extensive testing to show that in 0.6 seconds it is possible to correctly classify any type of home electrical appliance 99.9% of the time. This allows us to know what type of devices are connected and how they may be controlled.

(2) Secondly, after we know which devices are connected and active in the home, the most important factor towards effective control is occupancy information. Unoccupied rooms can simply turn off all non-essential devices, while occupied ones can still perform controlled reduction of power consumption. We achieve occupancy detection by exploiting the ever increasing number of WiFi devices by looking at the power consumption of a WiFi router. We show that it is possible to correlate the power consumption of a WiFi router with the number of people in a room, by extracting multiple feature using a novel short aggregate filtering method. We conduct several months of measurements at different locations and demonstrate that it is possible to correctly predict the number of people in a room 93% of the time.

By combining the fast classification of electrical appliances with the WiFi inspired approach for occupancy detection we are able to create system which can retrofit old buildings and improve new smart home designs to reduce electrical waste and provide peak demand relief without affecting the user.

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Chapter 1

Introduction

1.1 Background

The electric grid [1–3] is a complex system which controls the flow of electric power from the point of generation to the point of consumption in such a way to insure that certain parameters such as voltage and frequency are kept constant all the while insuring that the electrical production, as closely as possible, matches the electrical consumption. There are many aspects by which the electric grid can be defined, but when trying to distinguish the current one with the one we want to achieve there are several defining points.

1.1.1 Classical Electric Network

The current pre-transition network Fig. 1.1 is first and foremost defined by its central control approach. The best example of this would be any system where the service of providing electrical energy has not been privatised. Especially for smaller countries, this means that there is only 1 electrical company which does all the management, maintenance and long term planning. Usually, reagins will be centralised into one regional control center which will try to ensure that both the industrial sector as well as the residential users are satisfied and that he level or power quality is met from both the high voltage transmission lines as well as the low voltage neighbourhood lines.

Short term electrical production is usually planned 1 day in advance with any unexpected demand usually being phoned in and changes being done on the fly. Long term planning is done by assessing the costs and benefits of large scale investment over 5 to 10 years. Due to the lack of information, historical models are strongly used which are satisfactory in most situations, but usually create a much larger than desired production overhead. This is tolerated since unexpected events like sport tournaments, natural disasters or other such unprecedented event can results in much higher power consumption and a potential blackout. This is much less desirable since lack of service means lowered profits, increased maintenance costs and well as unsatisfied customers.

There will also be only a single market for buy and selling electrical energy, usually regulated by the government and influenced by the cost of materials and labour. Consumers have very little choice or influence over the price and are therefore highly dependent on the whether or not the government has made enough investments into the electric grid to keep costs low enough. Large consumers do have some negotiating power for wholesale of electrical energy and can be asked to reduce their power consumption at times to help

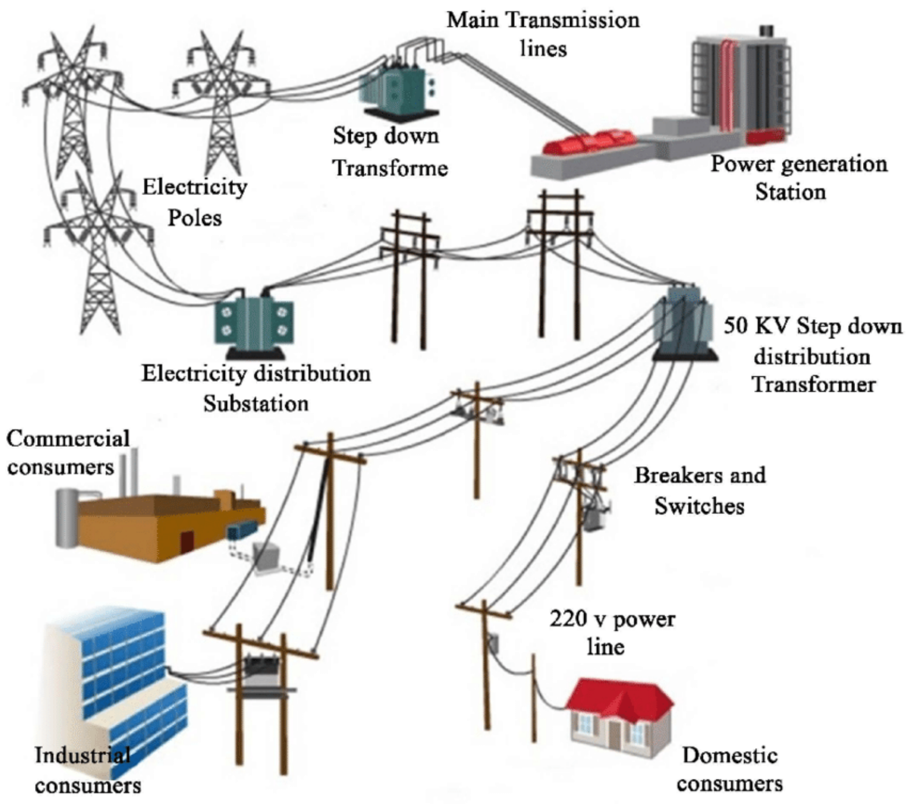


Fig. 1.1 Classic electrical grid

balance the load, but usually cannot freely choose to participate in selling their electricity without explicitly coordinating with the electric company.

Lastly production and consumption completely separated. A user will in almost all situations fully buy all the electricity they need from the electric company and will almost never participate in the electric grid. In some situations, depending on the laws [4, 5] and regulations, self production from generators and solar panels can be restricted to insure that the stability of the local low voltage network is not threatened or to prevent potential islanding. This is a situation where due to the electrical generation of an unknown unregistered user, the electricity starts unexpectedly flowing back into the network and can cause potential risks to the crews in the field trying to do repairs who were expecting a deadline.

1.1.2 Smart Grid

Smart grids [6–8] Fig. 1.2 on the other hand, use information technology to overcome their limitations. Control is no longer centralised but distributed. This is usually achieved in the form of much smaller microgrids, which can cover anything from a single house or building all the way to residential block or very small town with up to 100 people. These network try to be as self sufficient as possible, with even the possibility to go of the grid if needed. Electrical distribution is controlled locally as if there is a independent grid within the much larger national electric grid. This has many benefits since it makes the grid more resilient to larger fluctuations, easier to repair in case of a malfunction and gives the option for users to be more self sufficient.

Production is also more diversified. This is the driving force of the smart grid which we touch upon more in the following section; but the ability to integrate multiple types of different sources which produce electrical energy creates benefits as well as challenges. The price of electricity becomes less influenced by global price changes, but predominantly it also allows small investors to play a role in the electric grid, since construction companies and families can install their own solar panels.

Single markets turn into transactive market. One of the main characteristics of transactive markets is real-time pricing. Due to the smart metering and other information technologies it becomes possible to gather consumption information more frequently. This in turn enables the electrical companies to create prices which can be calculated much faster and for shorter periods. By doing so, electricity can be sold with a dynamically changing real-time price somewhat similar to how commodity prices get optimised on the stock market. The goal is the try to use pricing as a lever to influence user behaviour and motivate people to use electricity when the price is lower.

Lastly, with the aforementioned ability of users to buy an install solar panels by themselves, this can also maker users into producers and sellers of electricity during times of low use. With slow and increasing penetration of not only solar panels, but battery storage as well, new avenues are opening for users to use heat pumps, battery storage and car batteries to gather store and sell electricity to their neighbours, no longer being fully dependent on the electric companies.

1.2 Motivation

In this section we would like to discuss the driving force behind the conversion of the electric grid into the smart grid, namely the increased penetration of renewable sources of electric production. Afterwards, we introduce some of the research fields within the scope of smart grids and define how the scope of our research.

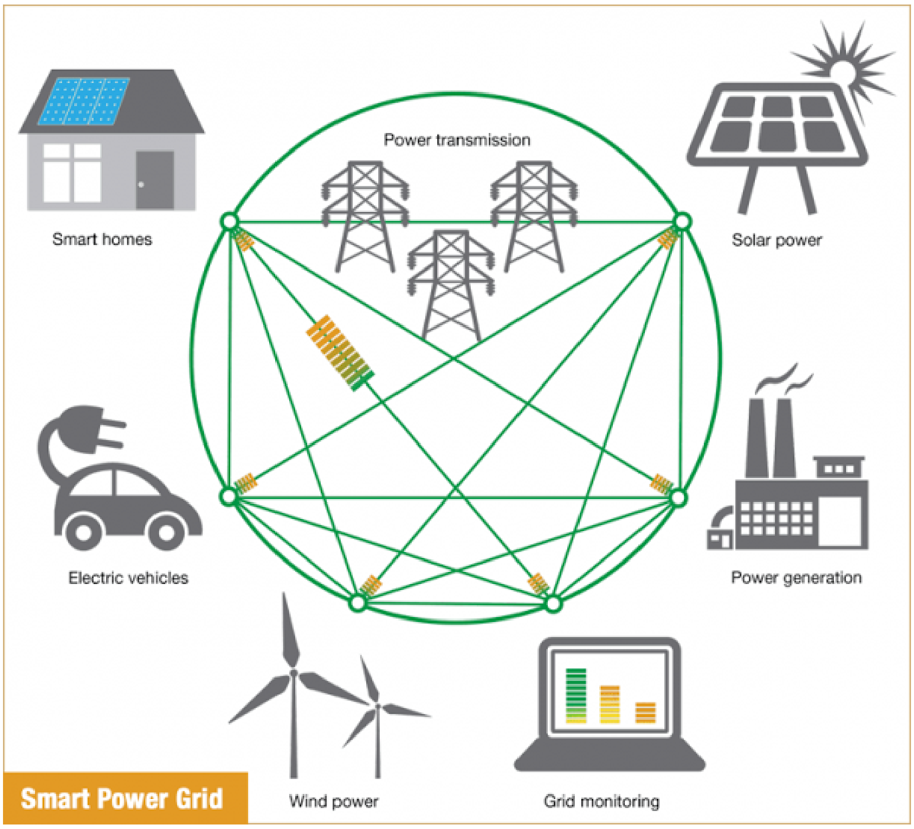


Fig. 1.2 Concept of a Smart Grid

1.2.1 Increased Renewable Penetration

With the creation of the atomic bomb towards the start of the 1940s, the general impression of many scientists, science fiction writes and the general public in the west during the 1950s and early 1960 was that society was progressing towards a new power revolution, similar to the one that the steam engine created. Unfortunately, fusion and it's promise of infinite energy was never achieve due to the technical challenges and financial cost. Instead, fossil fuels usage was increased to support the growing demand and the silicon chip created the information revolution.

These two outcomes perfectly set the stage for the next step of evolution for the electric grid. Due the high CO2 emissions and increasing speed of global warming, 0 emission power production with quick turnover became the go to technology with high political and economic support. In turn, ever increasing numbers of solar panel and wind turbines are being installed all across the world, with EU countries setting clear goals such as 20% energy production from renewable energy sources by 2020 [5]. With no slowing down

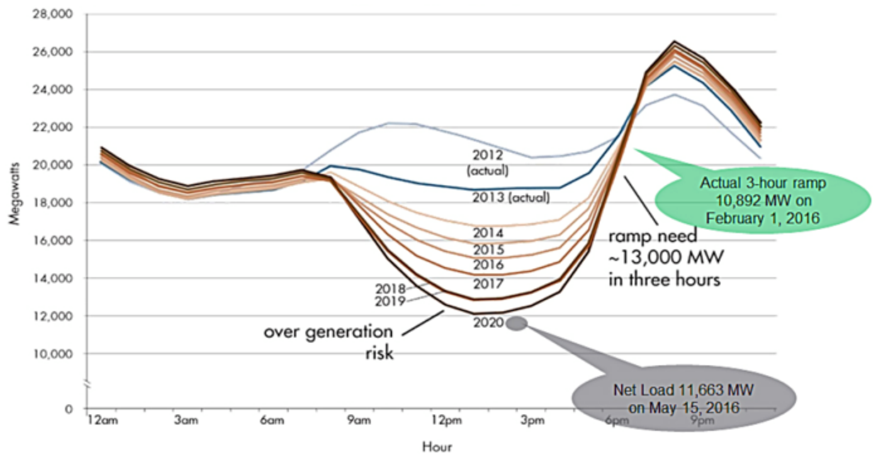


Fig. 1.3 California duck curve

in sight, all countries are predicted to increase their renewable penetration rate over the coming decades. For example, 27% of Germany's electricity comes from renewables with the goal of at least 80% by 2050 [9].

While 27% percent may not seem as significant on a national level, this can easily account for 40-80% at a local level. With this in mind it becomes much more apparent how renewable sources, despite their favour, create stress and drastically increase the complexity of the electrical grid. One of the most famous examples being the california duck curve as shown in Fig. 1.3. Solar power can only be gathered during the day with usually peak production being from 11 in the morning until 3 in the evening. What this created is a trough during noon time and makes the ramping up toward the evening even more steep than usual. Since it takes time for any generator to start up and start operating at it's optimal rotation, trying to overcome the predicted 10 MW increase in 2 hours becomes increasingly hard.

While wind power can be extracted even during the night it is still highly variable with geography and weather. Lack of wind, similar to cloudy weather can easily remove up to several kW or electrical production without warning, potentially creating problems in the electric grid.

The suggested solution from this problem is also the logical continuation which we mentioned at the start which is information technology. This is one aspect which has been used by almost every other industry and is now being adopted by the electric companies as well. While we cannot do much about the stochastic nature or renewable energy sources

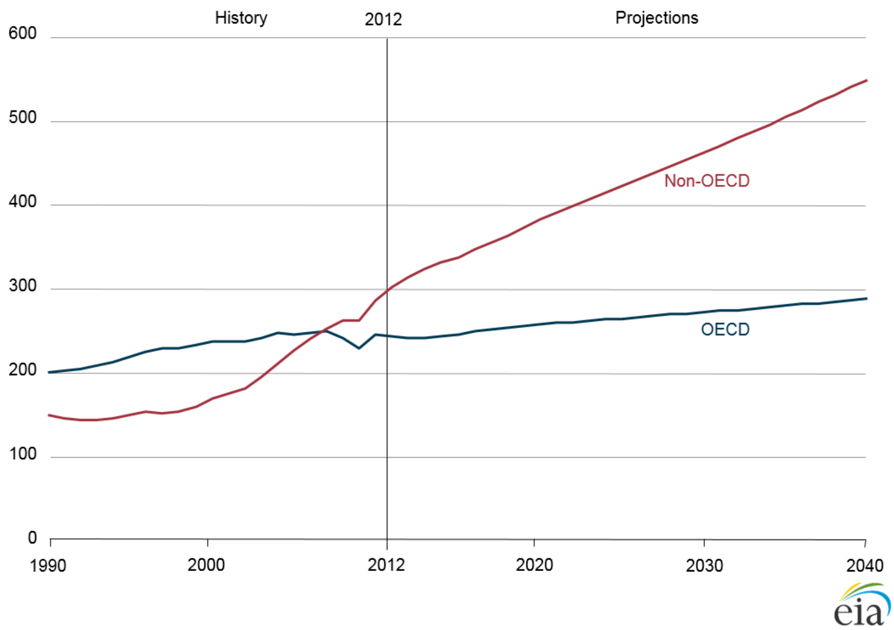


Fig. 1.4 Increased electrical consumption projection into the future

being introduced into the electric grid, there is a lot of ways we can use sensors, communication and information processing to optimise and control all the processes involved in the electric grid. By doing so we hope to only improve the current systems in developed countries but also, slow down the predicted demand of developing countries as well Fig. 1.4.

1.2.2 Research Scope

As shown in Fig. 1.5, the smart grid research field is very large. The IEEE PES (Institute of Electrical and Electronics Engineers, Power Energy Society) is also one of the larger groups and the fastest growing one. Much work has been done in recent years in areas such as production, transmission, storage and consumption. As to be able to better explain the initial scope of our research we will very briefly explain the areas of research, our focus and the motivation behind our research.

Over the last 10 years, much research had been done on improving renewable energy sources and production [10–13], especially solar. Production capacity has annually doubled, while costs have been going down by 50%. This in turn has made solar panels

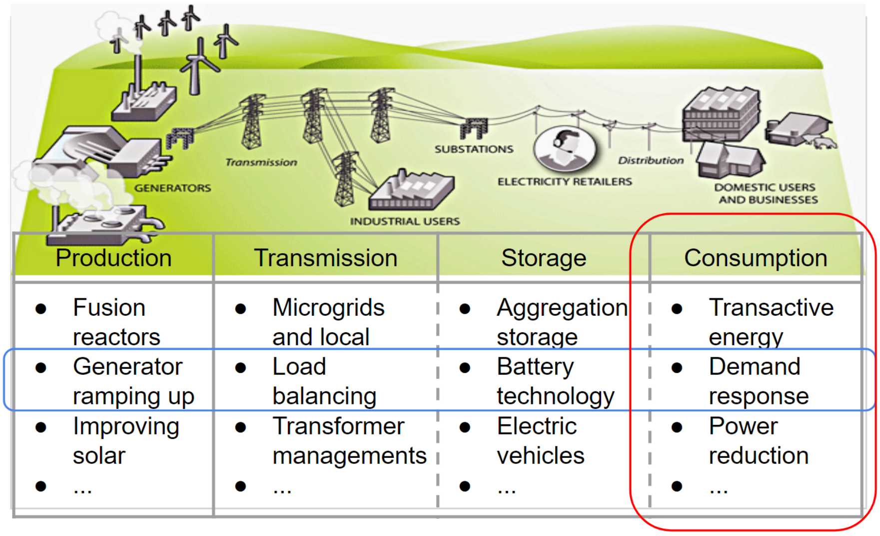


Fig. 1.5 Smart grid research field

a viable alternative and in some cases has even replaced plans for building natural gas burning stations, in favour of solar panel instalments. Also, new progress is being made in Germany and China in regards fusion reactors with new records for a stable magnetic containment field holding for several minutes.

Transmission networks [14,15] are also seeing improvement with multiple testbeds being created and several successful demonstrations of houses being able to automatically go off the grid without risk of islanding. Microgrids have been tested in small rural communities in Australia, USA and even actively cover one small island in Hawaii. While the number of people living in these communities is small, all these experiments have transitioned into part of the infrastructure.

Storage technology has has made great strides over the last 10 years. Initially considered an aspect which would never change due to a lack of progress, with the onset of electric cars, research in batteries has seen much improvement. Several large scale projects have been done in the United Kingdom and Australia where 3MW batteries are used for frequency control and peak demand cutting. While the cost benefit is still uncertain at the time of writing, batteries are predicted to find applications over the next 5 years as the price drops.

Lastly, consumption control [16–19] is being research to try to compensate for reduced and unsteady production. This includes many different and complementary approaches, such as transactive markets with real-time pricing [20–23], fast demand response for peak load reduction and frequency control, as well as energy reduction in the form of more energy efficient devices.

Our work focuses on the last section. We explore techniques which can improve demand side management and easily fit into fast demand response and transactive markets. Our assertion is that, due to the growing penetration of renewable energy sources, requirements for demand response will keep increasing. To this end our research tries to contribute to scientific advancement of the field.

1.2.3 Transitional technology

As it is to be expected, there numerous private sector companies who are also developing products to meet the needs of demand side management Fig. 1.6. This includes different products such as smart lights, smart thermostats and many other such devices where can be both remotely controlled as well as programed to follow time schedule or even price changes given the proper input. Given the fact that this is a growing market, there are many small companies and startups which have created such products alongside already well known brands. The result is an almost uncountable number of devices which are incredibly difficult if not even outright impossible to interconnects. A common occurrence when any new technology comes to the market. Compounding this problems is the fact that every company is currently seeking to create its own monopoly. This can be seen in very high levels of vertical integration between a company's product line, while interoperability is rarely discussed [24].

There are several non-profit organizations [25–27] as well as academic institutions were are trying to push for open standards. The best example is the openADR ALLIANCE which has gathered a large number of power companies and some manufacturers to agree to use the same set of protocols when trying to connect to a device from the outside with a goal of controlling it. Also, there are national movements [28, 9, 29–31] such as ECHONET in Japan to get all manufacturers to use the same standards for demand response management. Unfortunately, the growth at the moment is far outpacing any consensus on what the best approach is for current and future technology, creating a vacuum for the foreseeable future.

Lastly, there is a substantial cost of switching consumer electronics. Most people will not be inclined to buy a new oven of refrigerator unless there is a clear need to do so. This means that whatever change is going to occur over the next 10 to 30 years will be a

Fig. 1.6 Private sector companies and non-profit institutions focused on consumption control

graduate one where a lot of "dumb" devices will make up a large percentage of all user electronics in the near future.

To overcome this, with this research we focus on creating a transitional technology will be bridge the gap between a word of devices which have not been designed with control in mind and a future where most devices are predicted to have functionality which allows for smart remote control and management.

1.3 Thesis Organization

This thesis contains five chapters. It is organised as follows:

Chapter 1: Introduction

This chapter describes the background and motivations of this thesis to study demand side management in smart grids.

Chapter 2: Smart Plugs for Residential Power Management

This chapter defines the problem and scope of our research, explaining why we consider a smartplug based approach the best option to achieve demand side management. We also introduce why load classification and occupancy monitoring are required in such systems.

Chapter 3: Fast Active Sensing Electric Load Classification

This chapter presents how we achieved active sensing plug in load classification by using a TRIAC element. We show the distinguishability of items as well as how we were able to achieve real-time classification.

Chapter 4: Occupancy Detection by WiFi Power Consumption

This chapter presents our occupancy monitoring approach by means of a WiFi routers power consumption. We present our hypothesis, introduce a new filtering method for feature extraction and finally prove our hypothesis by experiment.

Chapter 5: Conclusion

This chapter summarises the contributions of this thesis as well as the suggestions for future improvements.

Chapter 2

Smart Plugs for Residential Power Management

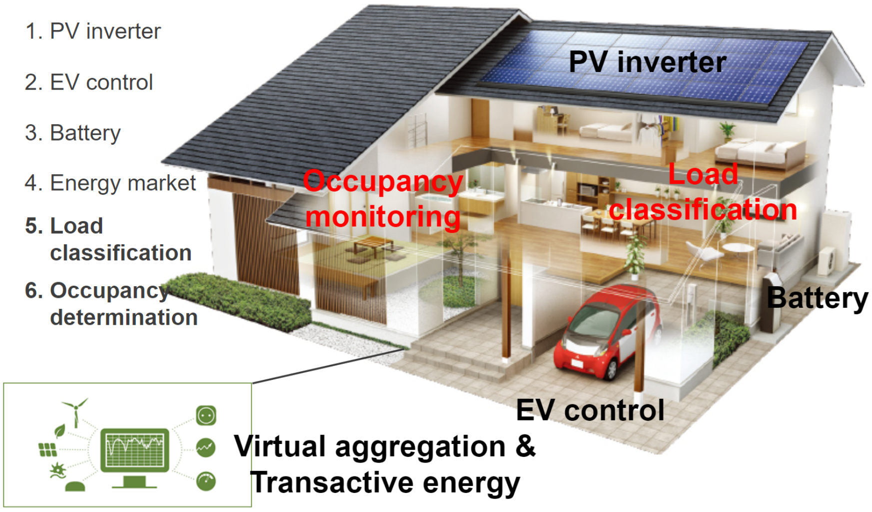


Fig. 2.1 Smart house management.

In this chapter we present research scope of this thesis while discussing the different aspects of residential power management. We define the benefits and need for electric load classification and well as occupancy detection as a means of presenting our case for a smart plug based approach for controlling a smart home. Finally we summarise our discussion.

Residential power management in this thesis is defined as the control and management of electrical consumption in all types of buildings commonly found within the residential or commercial sector, but primarily focus on accommodating people in daily activities. Examples would be, family homes, apartments, office spaces, waiting areas in public spaces and other similar spaces. As shown in Fig. 2.1 this can include multiple areas of research. Such as: 1) PV inverters, 2) EV control, 3) Battery management, 4) Energy markets, 5) Load classification, 6) Occupancy detection

- PV inverters are electrical circuits which insure that DC electricity from the solar panels if properly converted into AC electricity used in the house and properly released into the low voltage network to which the installation is connected to. The focus is to insure that no voltage imbalance occurs on the feeder line and that synchronisation time is as short as possible to no damage connected loads
- EV control focuses on ensuring that at on one time too many electrical vehicles are connected to the same low voltage networks feeder line. Since charging of electric vehicles requires a substation amount of electricity, it is easy to crash a local low

voltage network just by plugging in too many EVs. To avoid that, different sensing and scheduling protocols are researched.

- Battery research within a residential environment focuses on how to efficiently and effectively charge and discharge a battery storage system to fit within the residences needs. This usually fits in with the following point.
- Energy markets, such as transactive markets and virtual aggregation include research which deals with agent systems trying to find an optimal solution to sometimes NP problems. The idea being to optimise regional supply and demand by taking into consideration many local production and consumption nodes
- Load classification tries to correctly identify electrical loads within a house by looking at the electrical power consumption and matching a signal to a device. This is usually achieved by different method of signal separation from an aggregate smart plug
- Occupancy detection uses different techniques to estimate the number of people occupying a space as a means of managing the power consumption. This can include, turning off devices or managing the power level.

The scope of this paper will focus on the final two categories. We chose these two fields due to our desire to focus on reducing power waste and providing a non-disruptive way of managing electrical power consumption. Most demand response systems unfortunately share a common problem, which is that they tend to be either highly disruptive to the end user, simply shutting off devices when the demand is too high, or are very limited in their applicability due the limited usefulness. With this in mind, we wanted to expand as much as possible the number of devices which could be controlled at any given time without creating any overhead to the end user.

2.1 Requirements for Demand Response

Demand response functionalities are still in early stages of development, but due to their huge potential, they are considered an important aspect of the smart grid. To this end in this section we will discuss some of the current requirements for imposed by different countries regarding demand response.

In 2008 under president Obama Executive Order No. 719 - Federal Energy Regulatory Commission was signed into law. This set of law imposed rules for and even greater liberalization of the electric grid as well as provided certain guidelines. To increase the demand response potential the following problems were stressed as being of importance: lack of real time information sharing, lack of advanced metering infrastructure, high cost of some enabling technologies, lack of interoperability and open standards, lack of customer awareness and education and others.

A similar law was instituted by the European Commission under the Energy Efficiency Directive (EED) - 2012/27/EU. While the implementation was left to each individual country and there are significant differences in the level of progress, similar guidelines to that of the USA were set for those countries which more developed demand response system. This included: granular availability requirement and short call duration to insure closer to real-time pricing and full aggregation of consumer load and no minimum load requirement to increase the demand response potential. As stated in the guidelines the following action should be taken.

2.1.1 Real Time Information Sharing

When responding to an emergency event on the system, ISOs are not always aware of how much of a particular demand response resource is available, or even when it has been called by the utilities. This lack of real time communication among ISOs, utilities, and aggregators limits the value of demand response to ISOs for operational planning purposes and potentially leaves valuable demand response resources sitting idle at a time when they are needed most. According to the FERC 2007 Demand Response Assessment, this was found to be an issue during heat waves in the summer of summer 2006 in both California and the Midwest ISO.

2.1.2 Lack of Cost-Effective Enabling Technologies

There is a diverse menu of technologies that can improve customers' ability to provide demand response, but these technologies are not yet all cost-effective. Examples of enabling technologies include smart thermostats that respond to high prices with an automated adjustment to their setting, whole house gateway systems that allow multiple devices to be similarly made price sensitive, advanced energy management systems in commercial buildings and process control systems in industrial facilities that can reduce load when needed. Customer awareness of these technologies is low and given the low level of market penetration, the cost of the technologies is high, creating a unfavorable situation. It has also been argued that the marketing infrastructure (the value chain from the equipment manufacturer to the retailer and the installing contractor) is in its infancy. A "market transformation" initiative akin to that pursued in the energy efficiency business may be needed to allow rapid penetration of smart (price sensitive) control technologies in customer premises that would allow them to see the full benefits of demand response.

2.1.3 Interoperability and Open Standards

Interoperability and open standards refer to the manner in which various technologies, such as meters and in-home enabling technologies, communicate. If advanced meters contain communication chips based on open communication standards, such as ZigBee, it might be possible for consumers to purchase in-home control and information devices that would automatically communicate with their meter and that, in turn, would help automate or otherwise increase demand response. Open standards might also reduce costs by encouraging competition among technology providers to obtain large scale meter and other technology contracts. A number of jurisdictions and/or utilities are building open communications standards into the functional specifications for AMI systems that they will consider. On the other hand, some have questioned whether the meter should serve as the gateway to Home Area Networks (HAN) and other devices, because this might allow utilities to control the technology and access to meter data by third parties could be limited.

All of these techniques move the market towards a real time pricing. As shown in Tab. 2.1 this is a market driven approach which aims to influence user behaviour by penalizing and incentivising them to use certain types of appliances in certain times by changing the rate at which electricity is charged during different times of the day. An example of this would be charging higher rates for electrical heating due to its inefficiency, charging lower rates for air conditioning units during off hours to regulate temperature or penalizing user electronics during peak evening hours. To reach this type of real time pricing precise classification of electrical loads is needed.

2.2 Electric Load Classification

Electric load classification is the base starting point for demand side management and has multiple benefits to both users and other stakeholders. It has been shown that showing

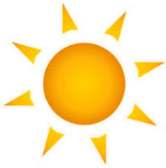
			
	0.9x	1.1x	0.9x
	1.0x	1.2x	1.0x
	1.0x	1.0x	1.1x

Table 2.1 Real time pricing situation where different rates are applied to appliances during different times of the day

that if users know how much electrical power each device is using instead of just showing the aggregated power consumption, use behaviour changes. It allows for an educated decision which devices use the most electricity or if there is any damage on device.

Electric companies and more specifically virtual aggregators can use this information to regulate frequency and reduce peak loads. A virtual agregator goes about this by looking at multiple smaller users and aggregating their power consumption. This in turn, allows them to shift much larger amounts of power consumption in time then any small user could do by themselves. The more devices that can be classified, the more devices that can be controlled, the greater shifts in time and peak consumption can be made.

Also, distribution of electrical consumption based on devices and type of device is of great interest to policy makers as well. From Fig. 2.2 we can see that about 30% of all the residential power consumption in the USA is unknown, with this being almost double in commercial sector. Better understanding of power consumption allows for more targeted policy and regulations and can sometimes result in interesting findings. For example,

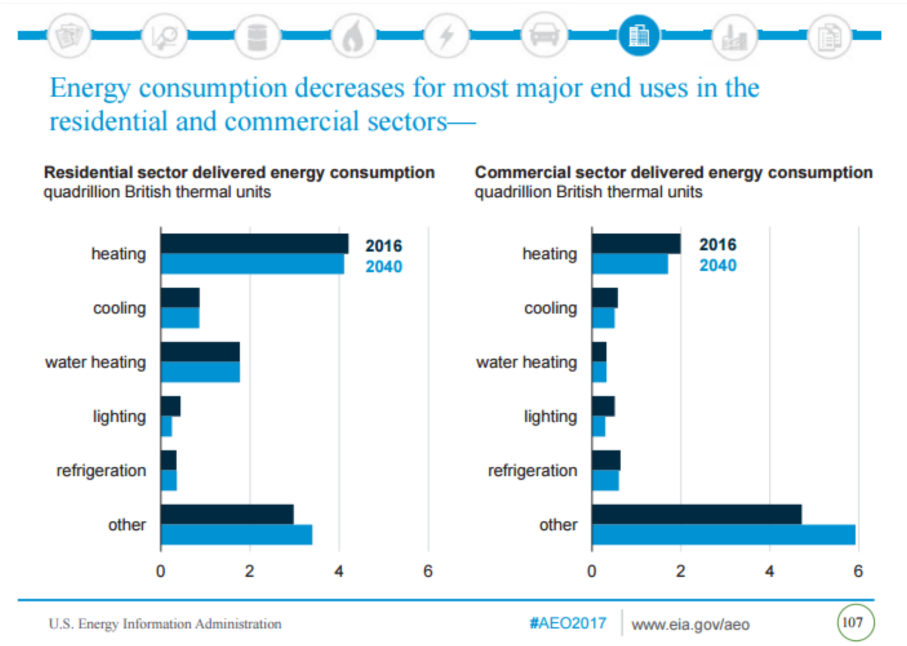


Fig. 2.2 Distribution of energy consumption by known device type

policy makers pushed much harder for power saving in gaming computers once it was discovered that high end configurations can easily push up to and over 300 W.

The ever increasing number of small devices is complicating classification which usually has greater problems classifying small load. These are also the types of devices which most prominently have batteries and would fit in very nicely with peak load reduction since they can be easily shifted in time. Secondly, a large number of high power consumption heaters such as irons, hot plates, small heaters is quite often not plugged into the socket until the moment it is used. After which they are usually disconnected or not used. These types of devices and any potential new ones which are not plugged in for long periods of time require a fast classification in order to be quickly identified and controlled.

2.3 Occupancy Detection

Occupancy detection is an important aspect of residential power management since it allow us to much better control devices then we usually could. In [32] authors look at two types of buildings. One was a gold standard certified green buildings, designed and built for energy efficiency. The other was an old campus building with no special design. Both did have a HEMS to regulate air conditioning and lighting. After one year of monitoring,

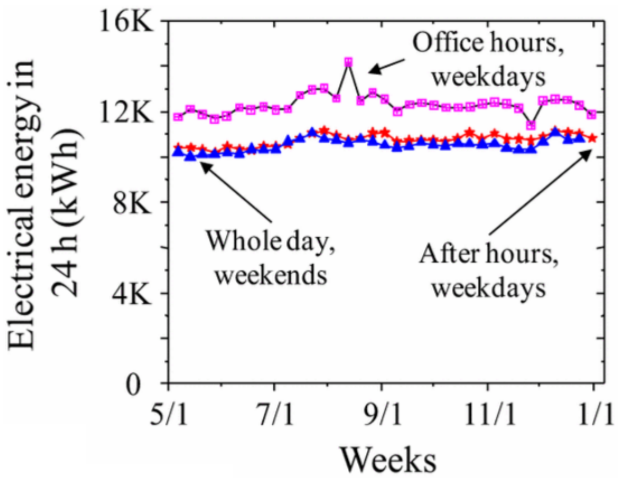


Fig. 2.3 Consumption of electrical energy over several weeks without significant change

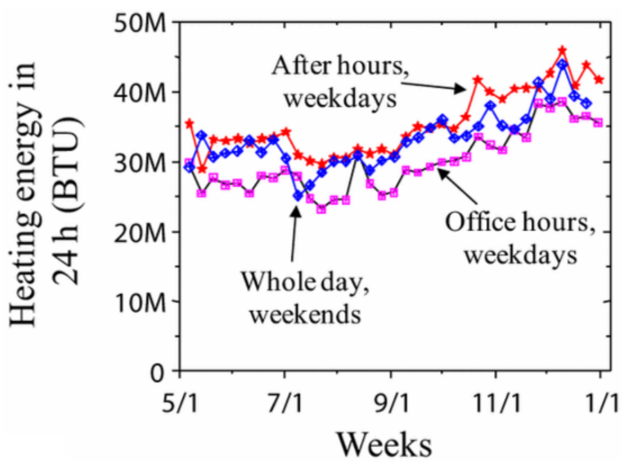


Fig. 2.4 Consumption of electrical energy for heating over several weeks without significant change

they were able to show that the power consumption did not change with the time of day. As shown in Fig. 2.3 and Fig. 2.4 there is almost no change from day to day in both the electrical energy and the heating.

The authors further continue to discuss that the biggest problem was the HEMS it self. There were no implemented policies to regulate power consumption. Most of the time, the power setting was set by someone depending on the need at that moment after which

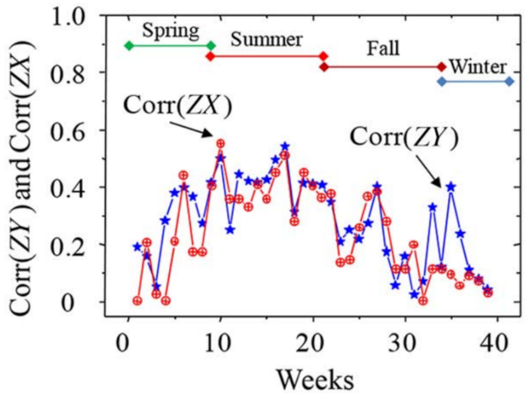


Fig. 2.5 Below 0.5 correlation between electrical energy and temperature, humidity

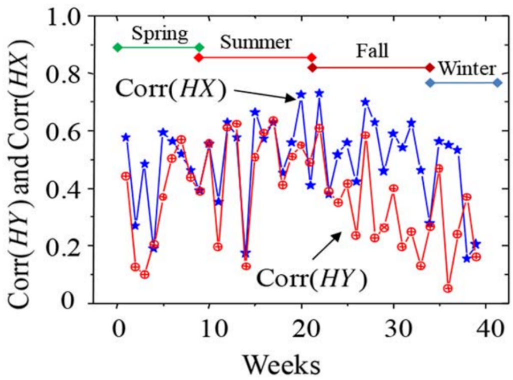


Fig. 2.6 Below 0.5 correlation between electrical heating energy and temperature, humidity

it remained the same until someone changed it.

They further demonstrate as shown in Fig. 2.5 and Fig. 2.6 that there is no correlation between the outside temperature or outside humidity and the electrical energy consumption or heating energy consumption, for the whole year.

2.4 Smart Plugs Towards Controlling a Smart Home

There are three main approach when trying to control power consumption of electrical devices in an environment: 1) Aggregate smart meter + actuator, 2) HEMS based on direct device access, 3) Smartplug based

- Aggregate smart meters are becoming a cornerstone for most electric grids. Despite high costs if interaction they do provide the electrical companies a much better and simpler way to collect data on their customers. This reduces the labor costs of an inspections and makes billing a much simpler process for the electric company. While they can oftentimes be very precise depending on the electronics installed, they are primarily designed for monitoring not control. An aggregate smart plug will monitor the aggregate power consumption of a environment, and by applying different types of learning algorithms or signal processing algorithms, it is possible to distinguish which devices are being used at which times. But, it is impossible to control them without using a completely separate system of actuators which would be able to interact with each device and turn it on or off.
- HEMS based on direct device control is a an example of ecosystem technologies. With the Internet of Things trend on the rise, more and more devices are able to connect to the Internet, cloud, or some other type of service. This means that it is possible to directly connect to a device and either turn in on/off, or regulate it power consumption. Most devices can also easily be fitted with a power monitoring chip which could report the power consumption and even regulate the devices usage based on it. Unfortunately, the problem quickly appears when we look at connectivity. Even if we ignore the fact that most devices at the moment cannot connect the internet and that even if all the new ones could it would still take many years to replace all of them, they are not connectable. Most makers of appliances are producing only appliances which are able to connect within their own ecosystem. There are no norms or regulations forcing everyone to use the same protocols and since everyone is racing towards a monopoly, in many case interconnectivity is intentionally obfuscated. Even approaches for trying to connect multiple devices have shown a high cost when trying to connect different devices in the form of APIs, different programing environments and time required to insure interoperability.
- Smartplugs are relative newcomer on the market. As shown in Fig 2.7, they are small devices which can be plugged into a wall socket, after which any device can

Fig. 2.7 Example of commercial smart plug

be plugged into them. They act very similar to the much larger and more powerful aggregate smart meters, but instead of measuring the entire power consumption of their environment they only measure the power consumption of whatever is plugged into them. This information is can be transmitted by wireless communication to a central aggregation point of distributed in a decentralised manner. Their biggest benefit is that they are able to easily control devices by simple turning themselves on or off. If slightly retrofitted they can also reduce power consumption of resistant loads such as heaters without turning the device off. In this regard, they are the only system which is able to not only monitor power consumption but also control plug in loads. While they might not be able to change the power state of certain appliances, they are nevertheless able to affect a much larger group of devices than any other approach

Given these, we consider a smart plug approach the most viable towards controlling residential power consumption due the limitation in controllability of interconnectivity

	Type of device	(ILMS) Smart plug	(NILMS) Smart meter
Plug in electrical loads	Heaters	Yes (%)	Yes (I/O)
	Small devices	Yes (I/O)	No
	Extension cord devices	Future work	Yes
Built in electrical loads	Building level air conditioning	No	No
	Neon lighting	No	No
	Lighting fixtures	No	Yes (%)

Table 2.2 Comparison between a smart meter and smart meter scope of applicability

compared to other approaches. While a smart plug approach is not all encompassing Tab. 2.2 it effectiveness is comparable to other approaches while being implementable at the present time. Making it the best option for a transitional technology.

2.4.1 Control Algorithm

A control algorithm for a smart home can take multiple variables into account depending on the goal of optimization. This can include optimizing for cost, user comfort or absolute consumption. While an analysis of this would be outside of the scope of this research a simple algorithm to reduce power consumption would be as follow a state machine from Fig. 2.8:

- Smart plugs are connected to electrical loads and create a network to communicate with each other or with a central control point
- Connected loads are identified and assigned values or a class. They are judged based on the following categories

  Can the device be shut down? (Is this a type of load which can be turned off or shifted in time. For example a monitor can be turned off if not used, a laptop could be shift in time for a short period, but a desktop PC cannot)

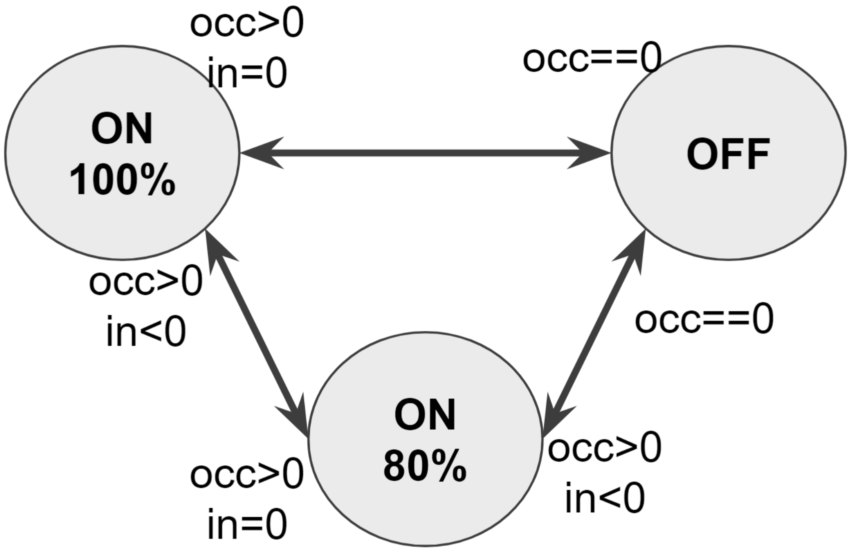


Fig. 2.8 State machine representing an example smart home control algorithm. Depending on the occupancy (occ) and external input (in) to reduce power consumption, the device is turned off, on or put in a lower power state

Is it a battery load / resistant load / other? (Battery loads can be shifted in time much more easily or even unplugged when full, while resistant loads can have their input voltage manipulated)

- Depending on the power consumption, the number of people in the space is determined.
- Depending on presence and aggregator signal information, smartplugs turn off or lower load power consumption

2.5 Summary

Any demand side management system which is want to optimise power consumption in such a way to reduce waste and be able to lower peak power consumption needs to be able to control electrical load, quickly classify and monitor occupancy. With this in mind we consider that:

- Smart plugs are the best approach to controlling legacy devices over the next 30 years

- Real time classification benefits real time pricing and tariff models as well as informs users
- Occupancy monitoring can significantly reduce electrical power waste

Our solution is an Active sensing and WiFi occupancy detection based smart plug power control system, the details of which are discussed in the following chapters.

Chapter 3

Fast Active Sensing Electric Load Classification

3.1 Background

The electric grid of the future is one which is moving more towards diversification of both production and location, affecting both how load balancing and how transmission is controlled. Increased renewable penetration is making load balancing more difficult due to inconsistent production as well as creating ramping up problems in evening hours. On the other hand, reliability and security concerns are pushing away from a centralised control system making regulators and companies concerned for cyber security and profit. To face the multiple challenges in the coming years, multiple technologies and approaches will be required in an effort to transition the network to a more efficient and sustainable smart grid.

One of the large aspect of this problem is load balancing. Simply explained, load balancing is a process of matching the total electric power consumption within a network with sufficient production. While electric power companies have been doing this successfully for decades, high wind and solar penetration create bigger oscillations in the production due to wind inconsistency and more stepper ramping up due to lack of sunshine in the evening hours respectively. While more electric production could solve this problem, it is unprofitable or even impossible to construct additional power plants which would operate for only short periods of time to cope with this problems. To supplement renewable penetration and in some cases reduce the power consumption, fast demand response (FDR) and storage techniques are proposed.

We propose a real-time electric load classification system for FDR to increase electric grid flexibility and improve the knowledge regarding electric consumption within households and offices. We achieve this by using a mix of unique smartplug design and machine learning. There are several reasons why we chose to focus on intrusive load monitoring (ILM) over other approaches. First off, we consider that battery storage and FDR are not mutually exclusive and solve different problems. Battery storage definitely has applications in frequency management and peak load cutting, but there are still questions regarding its cost effectiveness, as well as the fact that it is highly dependent on surplus production which deviates based on seasons and geographic location. On the other hand, FDR can reduce power consumption at any time, as long as it does not affect the comfort level of the user. We use smart plugs plugged into individual devices instead of smart meters which monitor the aggregate power consumption, due to their ability to control devices. A smart plug is able to easily turn on or off as well as partially reduce power consumption in a heater without turning off the device for short periods of time. Lastly we focus on real-time to allow for FDR to be applied to devices which are not always plugged in such as the ever increasing number of battery power electronics and traditional plug in heaters (hot-plates, iron, ovens). The added benefit of real-time classification is the ability to identify energy consumption in homes with greater detail. As shown in previous research, while there is good information on the amount of power used for heating, cooling and lighting in residential and commercial sector, the amount of miscellaneous power consumption makes up a large amount of the overall consumption as well as the fact that it is rising. Being able to know how much of this falls to battery devices and what type of devices, would open up new options for better power management and better targeted policy respectively.

Our approach is based on a unique smart plug design which used a bidirectional triode thyristor (TRIAC) to mask the input signal for short period of time. By doing so we are able to extract a much richer resolution from a static power signal which in turn allows us to more accurately classify the attached item to the smart plug in a much shorter time compared to other approaches.

3.2 Related Works

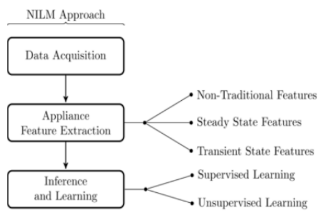
As we have discussed in the Chapter 1 and demonstrate in Tab. 3.1, electric load classification can be achieved by three methods. Prelabeled classification is the most simple approach since the appliance comes pre labeled. For Non-Intrusive Load Monitoring (NILM) and Intrusive Load Monitoring (ILM), represented by smart meters and smart plugs there is already an extensive body of research and a slowly growing number of papers respectively.

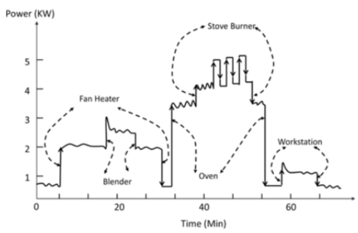
A large number of approaches to classify and control electrical loads have been proposed over the years. They usually fall into two categories: nonintrusive load monitoring (NILM) [33] and intrusive load monitoring (ILM) [34]. NILM is based around smart meters that analyze the aggregate electric consumption by monitoring the power line leading out of the apartment or house. ILM focus on smart plugs which are connected to a single device.

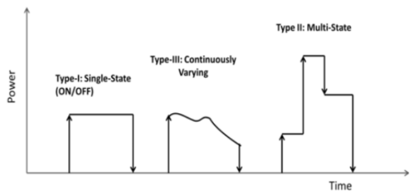
NILM based classification has been quite extensive over the years with impressive results Fig. 3.1. From a machine learning perspective are multiple ways to deaggregate and classify aggregate power consumption [35]. SVM [36–38], Bayes [39–41], HMM [42–44],

	HEMS (Home Electric Management System)		
Type	Pre-labeled	Smart meter (NILM)	Smart plug (ILM)
Approach & Scope	Knows devices only	Aggregate	Single load
Accuracy	Up to 10-100mW	Up to 1-10mW	Up to 10-100mW
Price	~200-2000 USD	~220 USD	~20 USD
Controllability	Yes	No	Yes


Table 3.1 Approaches to electric load classification







Learning Algorithm	Accuracy %	Training	Online/Offline	Scalability	Appliance Types
SVM	75–98	Supervised	Online	Yes	I & II & III
Bayes	80–99	Supervised	Both	No	I & II
HMM	75–95	Both	Offline	No	I & II
Neural Networks	80–97	Supervised	Online	Yes	I & II & III
KNN	70–90	Supervised	Both	Yes	I & II
Optimization	60–97	Supervised	Offline	No	I & II

Fig. 3.1 NILM classification approach and accuracy

Neural Networks [45, 46], KNN [47–49], and research into optimization [50–52]. Unfortunately, this approach lacks the ability to control devices limiting it applicability as a transient technology.

On the other hand, the decreasing costs of electronics and the proliferation of wireless communication specifically aimed at smart grids are making smart plugs an ever more viable option for controlling home appliances. They are especially beneficial for controlling legacy devices, which is important since electrical appliances usually experience a slow turnover rate. Because of this, different smart plug based approaches have been proposed

Type of classification	Time required	Accuracy	Cost	Approach
Mass feature extraction	1 day	95.5%	low	Innovative signal processing (pre filter, feature extraction)
Bayesian clustering	30 minutes	74.2%	low	
Random Forest + graphics card	~ several seconds	99%	very high (graphic card)	Hardware assisted signal modification + signal processing
Random Forest + TRIAC	~ real-time	98.93%	low	

Table 3.2 ILM approaches to electric load classification

in the recent years [53–56]. In [54] a machine learning approach is used to achieve very high classification accuracy rate of 95.5% with a Random Committee classifier and 1 days' worth of power measurements. [55] proposes an approach which uses shorter signatures of the electrical properties and is able to achieve 74.2% accuracy after 30 minutes. To overcome the low signal resolution, in [56] researchers have built a custom smart plug with a modified sound card which samples at a 96 kHz rate and is able to correctly classify with slightly higher overhead. While perfect for classification of static devices, these approaches are not so well suited for loads which are only plugged in during usage.

3.3 TRIAC based Classification

To be able to classify and control electrical loads we have created our own simple test bed which is able to measure the incoming electric power and modify the signal. The system is as follows [57].

As shown in Fig. 3.2 the input electric power is connected to a digital dimmer board. From the dimmer board two wires go out and into a power socket to which an electrical load is connected for testing. In addition, a clamp is placed on one of the wires to measure the current and two more lines are connected to each of the wires to measure the voltage. The controller is connected to the dimmer board, and is able to send the measurements to the PC.

The experiment was conducted in Japan, Tokyo, making the AC power line frequency 50 hertz and the waveform 100 volts. The dimmer board is used to mask the input signal which enables active sensing. We explain how this is done in detail in the next

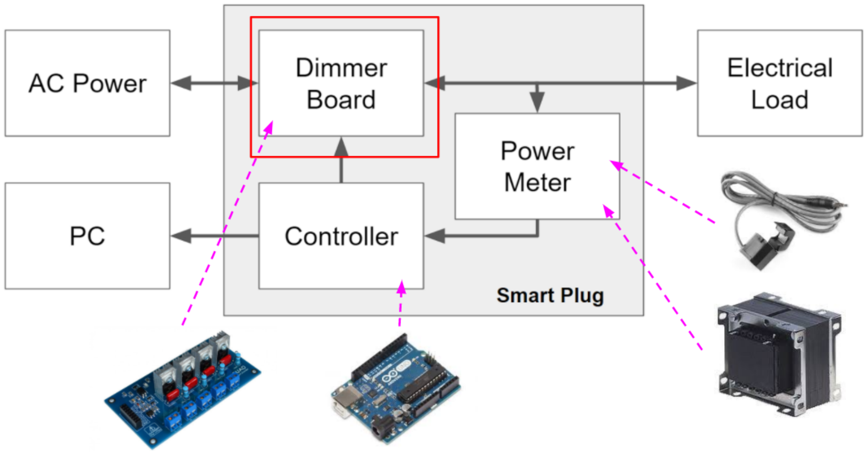


Fig. 3.2 Smart plug design

section. The controller is directly connected to the dimmer board, the electronics which make up the power meter and the PC. It sets all the dimmer boards parameters before each measurement and periodically samples the voltage and current from the connection between the board and load. Effective voltage, current and wattage it calculated from those measurements. After each session the controller can send the final values to the PC or wait until all the sessions are finished.

Fig 3.3 shows the electric schematic which was used for the electronics making up the power meter. For the controller we used an Arduino Mega2560 board. The signal was sampled every 0.2 milliseconds. An off-the-shelf wattmeter was used to check the accuracy of our power measurements. No significant difference was observed between our system and the wattmeter. The Arduino board was connected to a PC by serial connection for simplicity. Two dimmer boards were used during the whole process. A KRIDA Electronics [58] dimmer as shown in Fig. 3.4 with zero-crossing detection which only supported up to 5 amperes and a Research Design Lab digital dimmer board [59] as shown in Fig. 3.5 which supported up to 15 amperes. An oscilloscope was used to confirm that the signal masking was being correctly applied. We observed a clear output signal from the dimmer board correctly applied at each zero crossing for both boards. We do note that the TRIAC behavior is somewhat erratic for very low values, making us ignore the first threshold. Also depending on the setup and due to the fact that the dimmer boards have a limited number of thresholds, some of the measurements values are slightly different then it is to be expected and not as smooth as they should be. Nevertheless they are consistent over multiple measurements, meaning that hardware does not cause

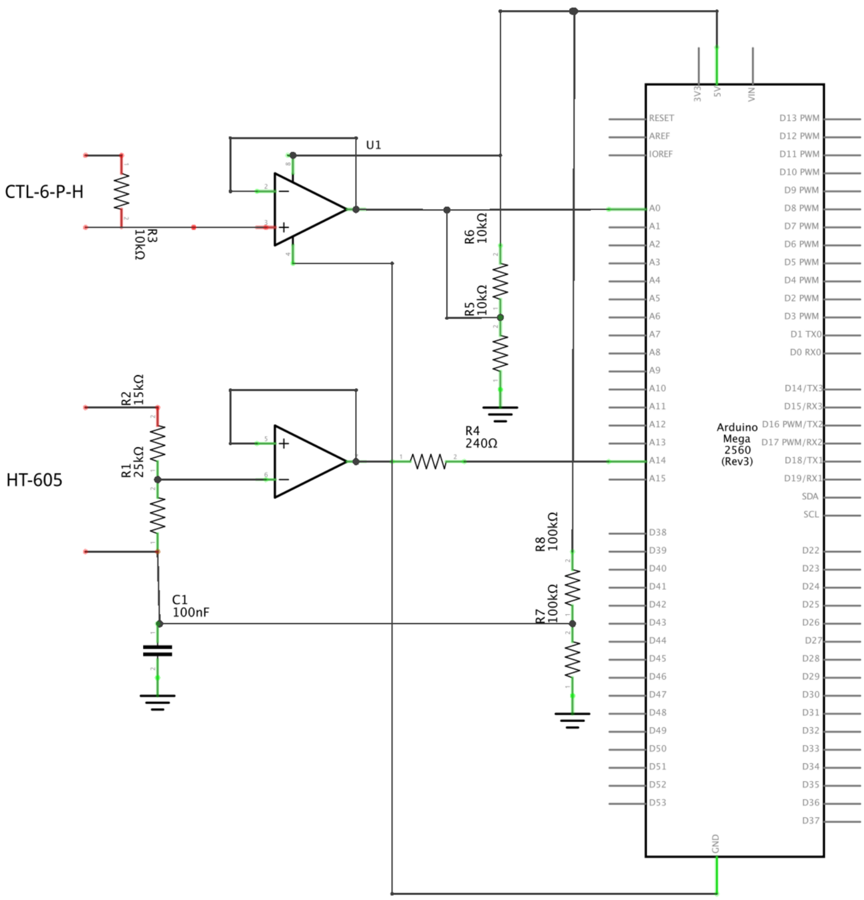


Fig. 3.3 Electrical schematic of smart plug

additional noise between measurements.

3.3.1 Fast Active Sensing

The idea behind active sensing is to slightly alter the incoming signal before measuring the output in an effort to generate more distinguishability in a real-time data stream. To achieve this we use a TRIAC to mask the incoming signal quickly, easily and without increasing the overall cost of the smart plug while allowing the option to control certain loads without turning them off to achieve greater savings during peak demand. In Fig. 3.6 we can see that TRIAC is combination of two diodes which allow for electric flow in different direction. Since the incoming signal has two fazes each diode is able to block electricity in one direction depending through which one the electricity is directed through. Since the diodes can only work in an ON of OFF mode they produce a cut signal like the one in Fig. 3.6. While a Variac would be able to produce a peak to peak reduction which

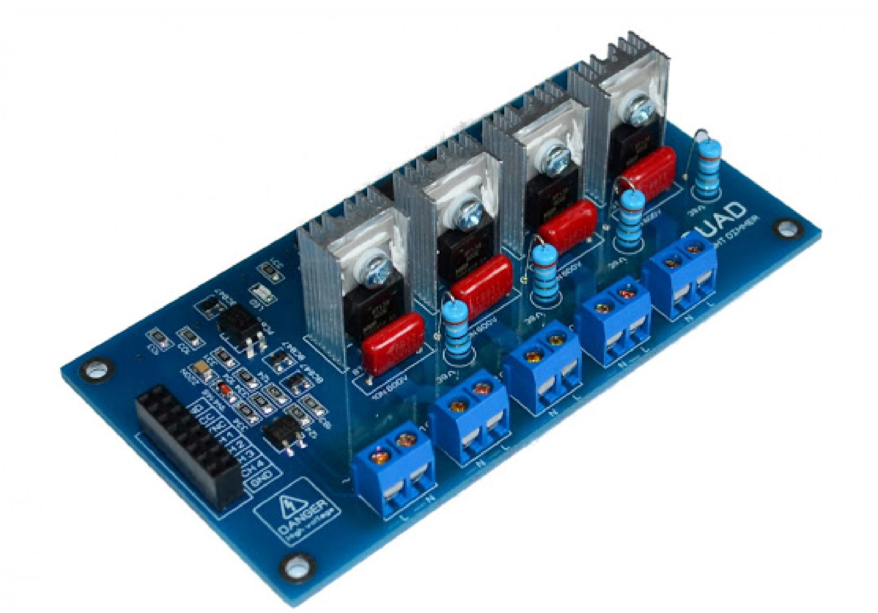


Fig. 3.4 KRIDA electronics dimmer

is usually considered a safer option, the costs and size would make the implementation near impossible.

Two parameters are controlled: the "Voltage cut" by performing signal masking and the "cycles" by performing period masking. Both of these are illustrated in Figure 3.8. In the first situation a TRIAC is set to active mode for 25% of the time and masks the voltage to 0 of each signal. In the second situation the TRIAC is set to 50% but only for 5 cycles. One cycle is represented by the time it takes for two rising zero-crossing events to occur. These means 1 cycle is equivalent to 20 milliseconds. By controlling these 2 parameters we can quickly modify the signal from very short periods of time and in turn create a large number of possible measurement for each device by actively sensing the changes in the power consumption during those times.

Figure 3.9 shows an actual masked signal. One square is equivalent to 5 milliseconds. The left graph shows a 10 percent cut for 2 cycles and the right graph shows a 45 percent cut for 1 cycle.

The benefit of this method as shown in in Fig 3.10 is that we are able to significantly increase data resolution in a very short period of time even on a very stable signal.

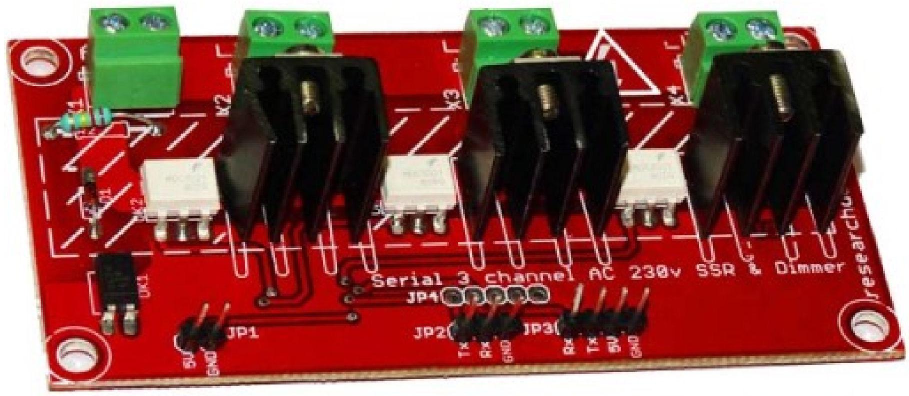


Fig. 3.5 Research Design Lab digital dimmer board

3.3.2 Device Distinguishability

As we can see in Fig. 3.11 and 3.12, each device has its own unique pattern depending on the electrical characteristics of the device. Resistive loads follow a mostly smooth, unbroken linear drop according to expectations. Electromotors follow a similar but slightly more oscillating pattern due to the swing nature of the motor. Inductive loads on the other hand show a much more scattered pattern reflecting the fact that the adapter is compensating for the changes in the input. Different types of other responses can be observed as well in case of other types of loads. A florescent light bulb will be either on or off depending on the current, as represented by the white center in the figure. Speakers on the other hand overcompensate at for the lower part of the cut ratio. It is possible to distinguish between different models of the same type of item.

Figure 3.13 shows the different power responses from an appliance. The horizontal axis represents the percentage of the signal that was masked with the TRIAC starting at 10

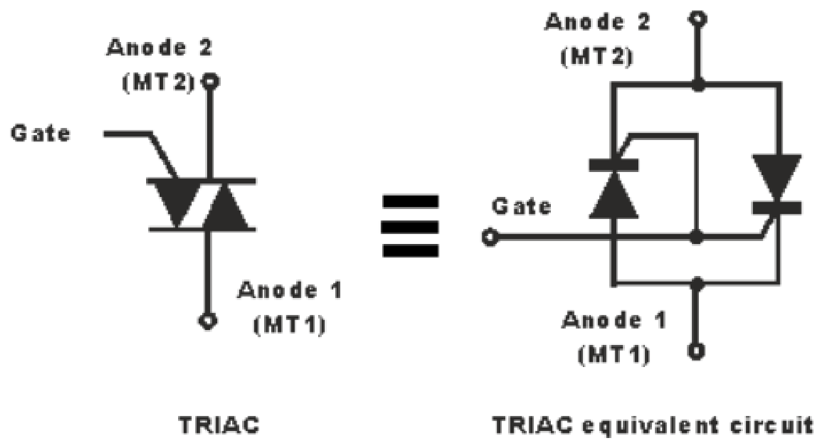


Fig. 3.6 Electrical schematic of TRIAC

percent and going all the way up to 95 percent in 5 percent increments. The vertical axis represents the number of consecutive cycles to which the masking has been applied. The numbers in each field represent the Watt measurement for the given session. Bright red are the highest measured values for the given instance while white represents the lowest measured values.

3.4 Evaluation

3.4.1 Data Gathering

Each measurement is compiled into three 17 by 20 matrices with the voltage, current and watt data respectively as shown in Fig. 3.11. Each electrical load was measured 100 times. A total of 32 items were measured as follows:

- Resistance loads

  Hot carpet

  Lamps x 3

  Electric heater x2

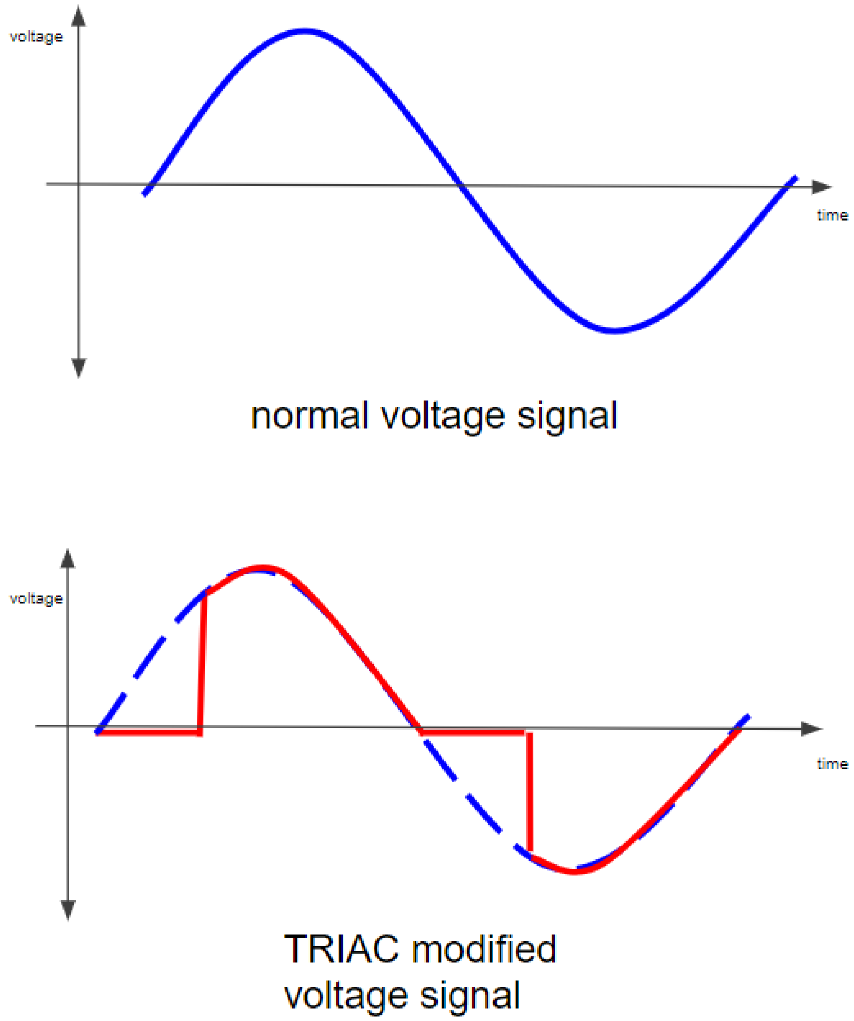


Fig. 3.7 Working principle of TRIAC

- Electromotors

  Small fan x2

  Big fan

  Vacuum cleaner

- Inductive loads & threshold

  Monitor x5 (2 types)

  Battery charger AA

  Blu Ray Player

  Fluorescent light

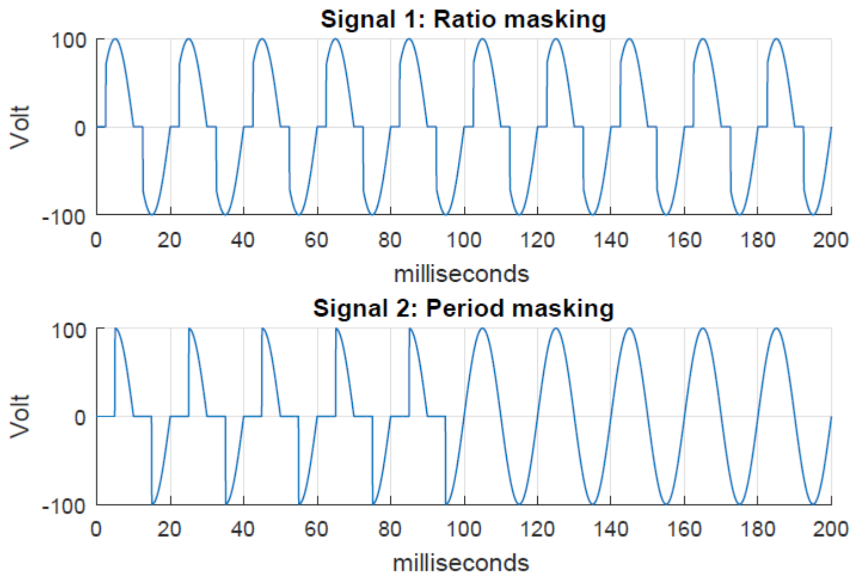


Fig. 3.8 TRIAC modification parameters

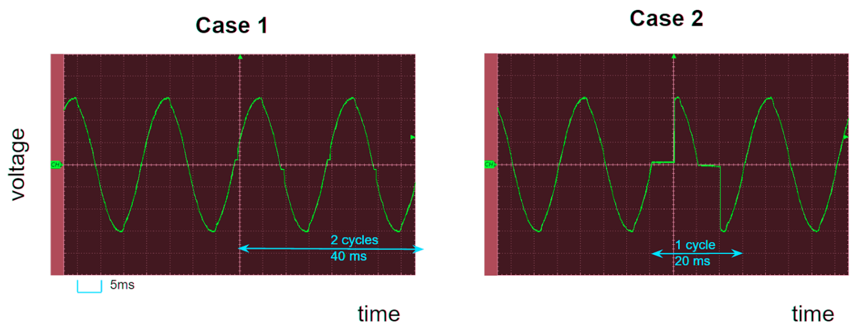


Fig. 3.9 Oscilloscope measurements of TRIAC signal manipulation

Humidifier x2

Lamp x5 (3 types)

Laptop

Smartphone

Speakers

TV x6 (2 types)

Each device has its own unique pattern depending on the electrical characteristics of the device. Resistive loads follow a mostly smooth, unbroken linear drop according to expectations. Electromotors follow a similar but slightly more oscillating pattern due to

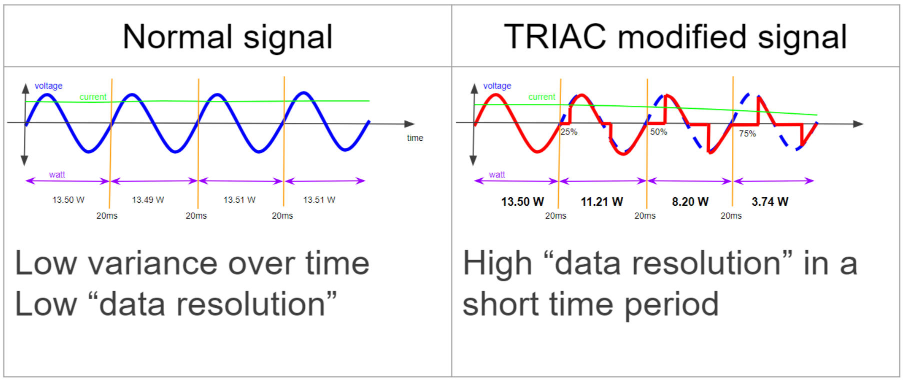


Fig. 3.10 Higher data resolution of a TRIAC modified signal

the swing nature of the motor. Inductive loads on the other hand show a much more scattered pattern reflecting the fact that the adapter is compensating for the changes in the input. Different types of other responses can be observed as well in case of other types of loads. A florescent light bulb will be either on or off depending on the current, as represented by the white center in the figure. Speakers on the other hand overcompensate at for the lower part of the cut ratio. It is possible to distinguish between different models of the same type of item.

3.4.2 Classification Algorithm

We tested out multiple classification algorithms using the R programing language and the provided libraries: ANN - (“neuralnet”), Support Vector Machine - (“e1071”), Random Forest - (“randomForest”), the C50 decision tree - (“C50”) and the extreme learning machine - (“elmNN”). We were guided by other works such as [60] as well practical time restrictions. While we are aware that there are some disagreements to the accuracy of [60], most of the criticism we were able to find tend to discuss suggest slight changes to the top 5 best algorithms, while not disputing that the best general purpose algorithms are: Random Forest (RF), Support Vector Machine (SVM) and ANN.

Table 3.3 shows the classification accuracy of each algorithm using the full data matrix and watt data matrix only respectably. For each of the 32 items, 70 samples were chosen randomly for training while 30 were used for testing. The C50 decision classifier shows the best classification accuracy at 98% followed by the Random Forest classifier, Support Vector Machine and extreme learning machine.

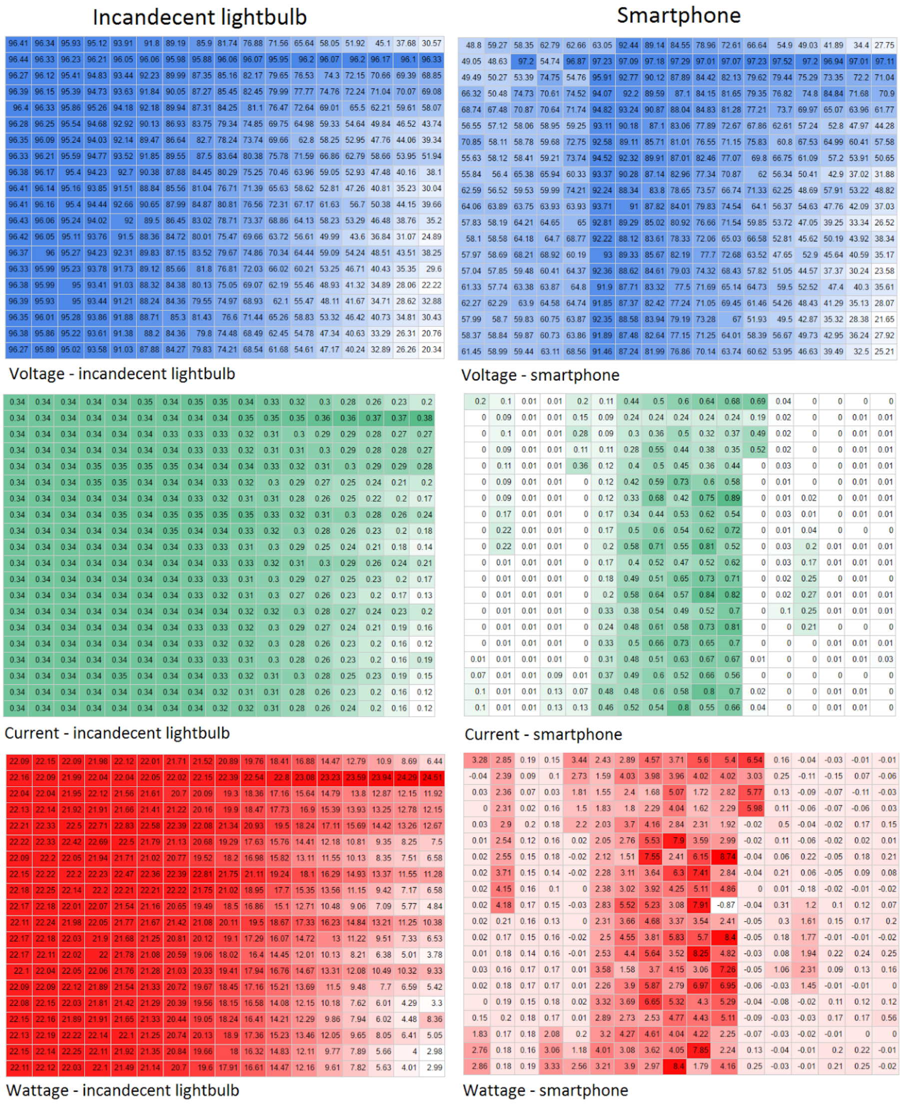


Fig. 3.11 Comparison of two loads while looking at voltage, current and watt

The extreme learning machine results were to be expected. A single layer neural network had problems converging, especially when nodes are not fully connected. The decision tree type classifiers give the best results. There is a slight difference between classification which uses all 3 matrices (voltage, current, wattage) and only the watt matrix. There is a difference of 2%.

Classifier type	**Wattage only matrix**	**Full matrix**
Support vector machine	87%	75%
Random forest	94%	83%
Extreme learning machine	5%	3%
C50 decision tree	99%	97%

Table 3.3 Classification accuracy of multiple classifiers

3.4.3 Classification Accuracy

The results of classification are presented in Table 3.4. The classification results show a 96.5% accuracy. All the devices are correctly classified with a high level of accuracy. From the 100 instances of measurement, 70 were used for training and 30 for testing. In addition, we also performed 2 types of classification. The first being on an appliance level where identical items such as same type TVs and lamps were grouped together. This represents our ability to inform the user of which device is active and how much electricity it is using. The the second we grouped all resistant loads, battery loads and any other miscellaneous ones together into just three groups. This represented the load classification interest from the viewpoint of the electrical company in regards to demand response. The results were 97.2% and 99.99% accuracy.

This means that our proposed classification method has very high accuracy for users to inform them of their residential power consumption, while having a near perfect accuracy for the DR providers. This is important because while users might be willing to tolerate some small margin of error, a DR provider might very well be liable to damages in it were to mishandle a device.

Electrical load	*TP*	*FP*	*Precision*	*Recalling*
1) Incandescent light bulb	1.0	0	1.0	1.0
2) Smartphone	1.0	0	1.0	1.0
3) Fan (1)	0.9	0	1.0	0.9
4) Laptop	0.97	0.015	0.853	0.97
5) UPS battery	0.87	0.003	0.963	0.87
6) LCD monitor	0.97	0.009	0.906	0.97
7) Speakers	1.0	0.003	0.938	1.0
8) Fluorescent light bulb	0.93	0	1.0	0.93
9) USB battery	0.97	0.003	0.967	0.97
10) Vacuum	1.0	0.003	0.968	1.0
11) Electric blanket	0.97	0.003	0.968	0.97
12) Fan (2)	1.0	0	1.0	1.0
Average	0.965	0.007	0.964	0.965

Table 3.4 Classification accuracy for C5.0

3.4.4 Generality, Scalability and Cross Validation

Further testing with different devices has shown through cross validation that the method is robust for most devices and can correctly classify independent of the manufacturer. The biggest drawback being unknown devices. For example, if the data set does not include old electrical appliances such a very old computer monitors, they may end up being classified as plasma TVs of the nearest similar groupe. On the other hand we have also tested and confirmed that that it is possible to distinguish between 2 identical objects. Due to the small differences in the electrical components on the circuit level the TRIAC response does ever so slightly differ from devices of the same model. Lastly, we have also taken measurements from different locations and at different times to check if there are any significant differences in the gathered data. We have found no significant differences between locations. In addition, we have also looked at the starting conditions for each items and have concluded that most user electronics electrical power consumption does not differ enough in the short periods of time needed to take the measurement. Higher power consumption items can possess multiple meaningful states, but could be easily distinguishable since they are most often resistant loads.

Real time classification was achieved by subsampling as shown in Fig 3.14. Instead of using the full instance, all 20 rows, we only used the first 17 measurements. These were chosen since they are the shortest measurement taking only 20 ms each. As shown in the graph each addition measurement lowers the misclassification number (error rate). The optimal point in regards to time is 17 measurements while surprisingly the optimal point for accuracy is around 34 measurements. We consider that this is due to potential overfitting because too many data points are used to define an object. The C50 decision tree classifier has been shown to outperform all other methods and for 17 measurements presents at 98.9% accuracy.

3.5 Summary

We have demonstrated that by including a TRIAC element into a smart plug it is possible to achieve up to 98% electrical load classification within 0.6 seconds. We show how input voltage manipulation through two parameters can create a unique and highly distinguishable watt power output. We conduct stress test to insure that device failure cannot occur, and apply machine learning on the datasets to find the optimal form of classification.

We show that decision tree classification can achieve the best results compared to other approaches. We confirm that it is possible to differentiate two identical items and that scalability is proportional to the number of device classes. In addition, by using subsampling we demonstrate that sampling time can be reduced without strongly affecting the classification accuracy.

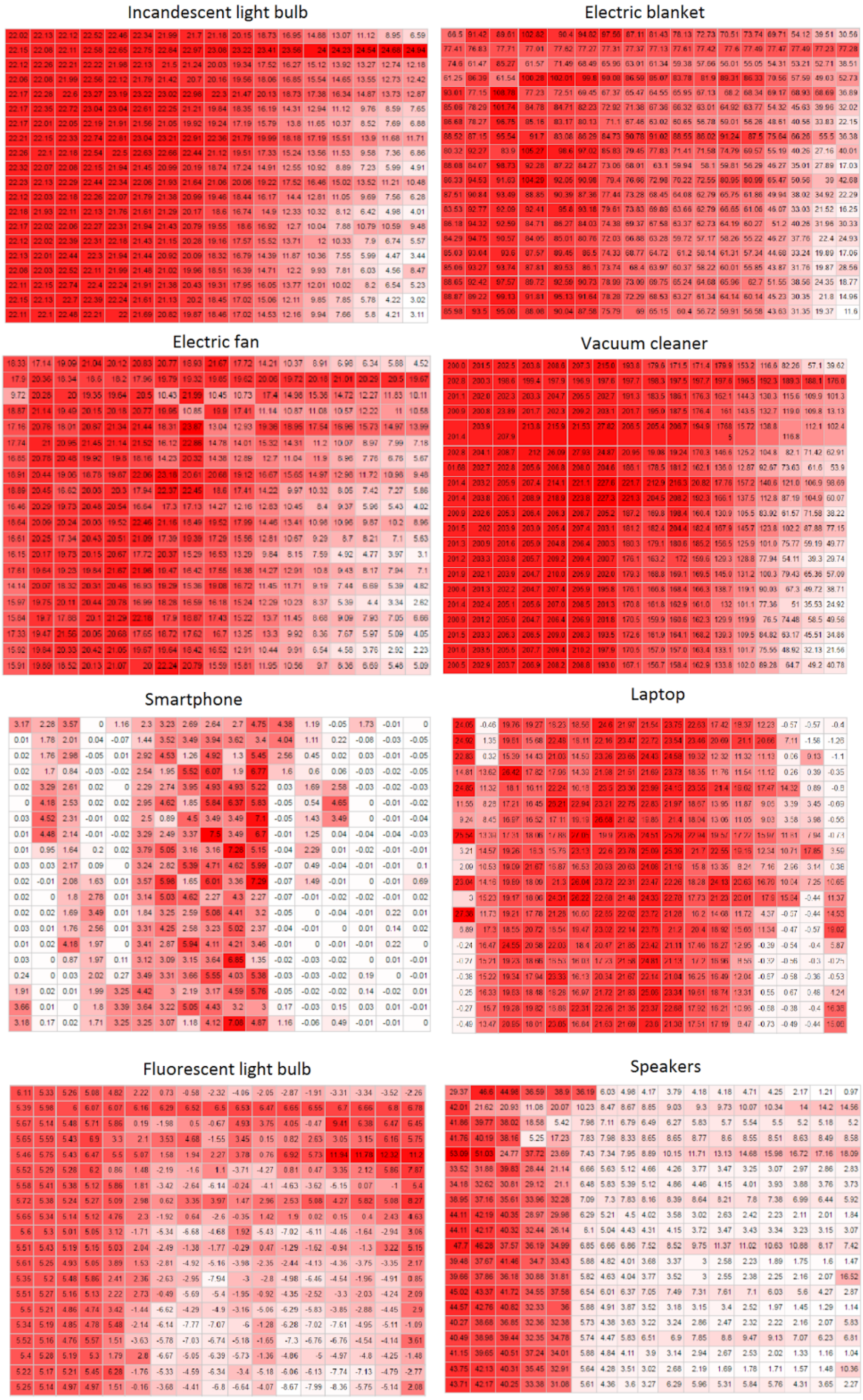


Fig. 3.12 Comparison of 8 loads while looking at watt

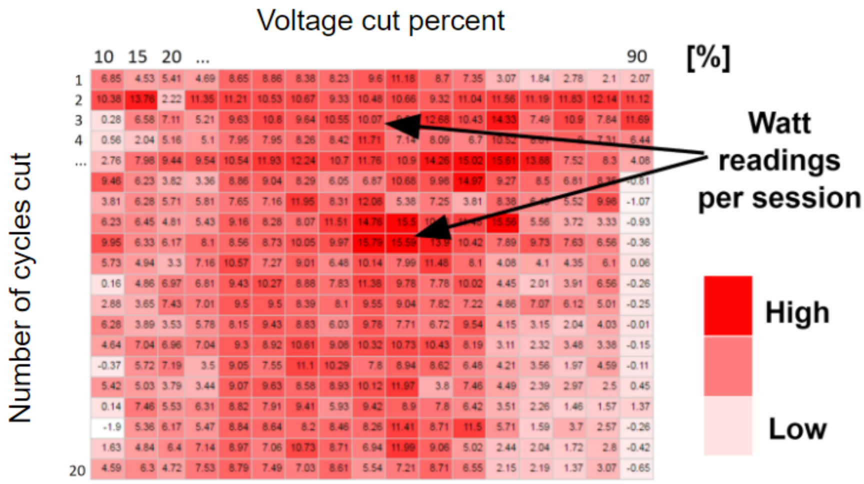


Fig. 3.13 Example of a unique dataset

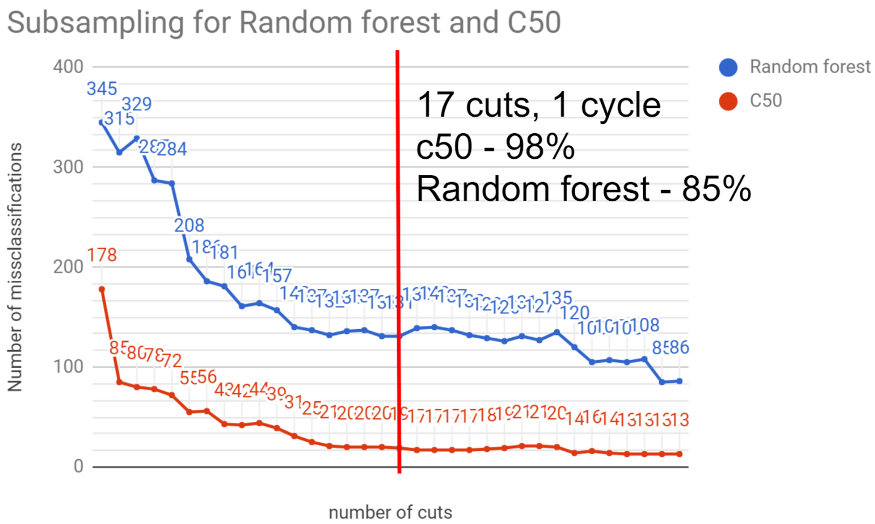


Fig. 3.14 Subsampling accuracy for Random Forest and C5.0

Chapter 4

Occupancy Detection by WiFi Power Consumption

4.1 Background

The increasing penetration of renewable energy production over the last two decades is creating an increasing pressure to the electric grid. The intermittent nature of renewable energy combined with the shorter and higher ramping up times is making balancing the electric grid an increasingly difficult task. Unfortunately, there are no easy and straightforward solutions, since increasing electric production is an expensive and long process. This means that multiple technologies will be needed to improve electric production, management and consumption if we are to transition to a sustainable and smart electric grid. With this in mind, our work focuses on reducing electrical waste on the demand side by creating a cheap and easily implementable system, which would be able to correctly estimate a room's occupancy and in turn adjust or turn off unnecessary plug-in devices. There are several reasons why we consider this problem important. We focus on electric waste in residential and office environments, since the residential and commercial sectors make up approximately 2/3 of national power consumption which translate to the fact that buildings take up between 40 to 60% of electric power consumption in developed countries [61–63]. Second, we target electrical energy waste because it is the least objectionable aspect of demand response since it equally benefits consumers and power companies, while having no detrimental effect on the consumer like restricted power usage [64, 65]. Also, multiple papers report high potential power savings from reducing electrical power waste. Lastly, we focus on presence detection to achieve our goal, since it has been shown that electrical power consumption in both regular and green buildings is not highly correlated with either temperature, or humidity, or occupancy [32]. This means that often an unoccupied building will consume the same amount of electrical energy as an occupied building, despite the energy difference of lighting, heating and cooling. This is due to the often rigid nature of Heat, Air Ventilation, and Cooling (HVAC) policies which are usually manually set based on time or the administrator's intuition.

4.2 Related Works

Multiple studies into human presence monitoring for electric power consumption and control have been suggested in recent years as shown in Tab. 4.1. These fall into several groups. First is the use of camera monitoring systems [66–69] such as the one in [70] where the authors achieve 80% occupancy estimation accuracy and report 14% energy savings, which are not significantly affected by the 20% error rate. While this approach can achieve

Approach	Benefits	Problems
Camera	High precision	Line of sight (20% error), Privacy, Cost
Passive Infrared Sensor	Cheap Privacy	Line of sight, "Cats" Installation
Electrical Consumption Monitoring	Privacy Line of sight not needed	Precision

Table 4.1 Comparison of different types of occupancy monitoring systems

high accuracy rates, it is very dependent on positioning. In our own experiments, we used cameras to determine the ground truth value of the number of people occupying a room. The issues with this approach includes: problems in correct identification due to blending with the background, blind spots in the cameras' field of view and low picture resolution and sample frequency due to storage limitations. While some of these problems might be addressed with better and more expensive hardware (fisheye lens cameras, on sight processing) the price is significantly increased. Also, we must address the problem of privacy [71–73]; since in each one of our experiments the participants expressed vocal disagreement to having a camera system monitoring them.

The second group of approaches focuses on different mixes of small embedded sensors like passive infrared sensor (PIR) and door sensors to monitor presence in real time [70,74,75]. The authors in [76] use this approach to infer occupancy with 88% accuracy, pointing out that for only 25 dollars' worth of sensors it is possible to reduce the electrical energy consumption by 28% in HVAC. This methods lacks the cost and privacy shortcomings of using a camera, but it does not address installation complexity and PIR sensitivity issues. Similar to cameras, we have also tried using PIR sensors, positioned at strategic entrances and doors, to monitor the number of people entering or leaving a house or office. We repeatedly found that sensors would mispredict due to people loitering next to them, leaving doors open and the fact that animals have no problems triggering the PIR sensors. While we are fully confident in the accuracy of previously presented research, we consider that the potential to implement these approaches is highly dependent on the layout of the rooms, line of sight and the positioning of the sensors.

Lastly, there are the electric energy monitoring approaches which monitor the aggregated electric power consumption of a building the determine occupancy as shown in Tab.

Approach	Results	Problem
Aggregate power monitoring	73.27% overall accuracy	limitation of aggregation
Virtual occupancy	78 to 93% home, 90% office	higher sensor costs
Extended feature extraction	83% and 94%, overall	long training time
WiFi router power monitoring	94% home, 99% office	user behavior dependent

Table 4.2 Comparison of different types of electrical usage occupancy monitoring systems

4.2. In [77–80] authors look at the electric power consumption from smart meters to estimate the points in time at which someone is at home. Electric load monitoring usually falls into two categories; non-intrusive load monitoring (NILM) in the form of smart meters which measure the aggregate power consumption of an apartment or building and intrusive load monitoring (ILM), usually in the form of smart plugs, measuring the power consumption of single device

In this section we look at ways to expand the benefits of an ILM approach (load controllability, low price, easy instability and privacy) with a high accuracy presence detection functionality. In our published work [81] we showed initial results that it was possible to estimate with high accuracy the number of people in an office environment by looking at the electric power consumption of several routers. This is different from other approaches which look at the WiFi signal's interactions with the surrounding area. In [82] the authors examine the channel state information between 2 WiFi routers to determine occupancy, while the authors in [83] use off the shelf components and achieve similar results by using the Received Signal Strength (RSS) of the WiFi router. One can also probe the traffic or connect directly to the WiFi router itself to determine the number of active devices if privacy is ignored.

4.3 Presence and Occupancy Detection

In this part we describe how we formed our hypothesis and describes our prefiltering process which allowed us to achieve the needed accuracy [84].

4.3.1 Hypothesis

The foundation of this work is based on the hypothesis that a WiFi router's power consumption can be used to predict the number of people in a room. In turn, this can later be used to regulate the power consumption in the same room by regulating the air conditioning and turning off all unnecessary devices in a room if the room is vacant. The control aspect can easily be solved by connecting the electrical loads through smart plugs or by accessing the home electrical monitoring system (HEMS), but the connection between a WiFi router's power usage and the number of people in a given room has yet to be fully researched. With this in mind we define several assumption which need to be true for our hypothesis to be valid. These are:

- A WiFi router's power consumption should be proportional to the amount of traffic on the network. - If a WiFi router power consumption is indifferent to network traffic than any consequent assumptions will be flawed.
- A WiFi router's power consumption should be proportional to the number of devices on the network. Since we are trying to determine the number of users on a network, all of whom can produce wildly differing network traffic, it would be beneficial if we could find some way to identify the number of devices as means of identifying lower traffic users and normal users from power users.
- The number of people should be accurately predictable from the power consumption of a WiFi router. The last assumption questions the likelihood of edge cases. Specifically, can we assume and in which situations that a presence of a person can be "observed" by looking at a WiFi's power consumption.

Assumption 1) can easily be confirmed due to the work done by the authors of [85] as well as our confirmation in Fig. 4.1 and 4.2. They have shown that the electric power consumption at an access point linearly increases with increased traffic rates for throughputs of 1Mb/s and higher. This also applies for the number of devices in a passive state as shown in Fig. 4.3. Specifically, this phenomena can be explained by looking at the distribution of control messages length 320-639 bits and their increased ratio in the overall traffic as shown by Fig. 4.4 and 4.5 respectively. For assumption 2) we already determined in [86] that multiple active high traffic devices are distinguishable and that they can be tracked on the network. This included confirming that switching between two networks just switches power consumption between routers as shown in Fig. 4.6 and that different router models do not affect the outcome, as they can be normalized to the same

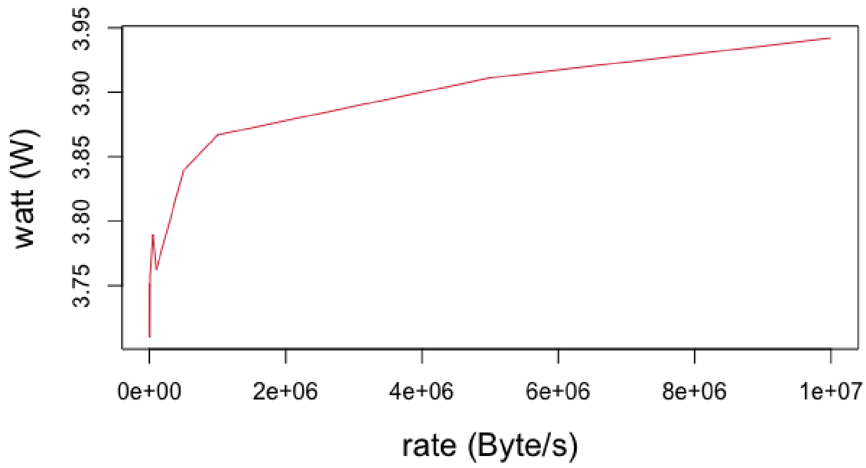


Fig. 4.1 Function representing the correlation between traffic and power consumption

values as shown in Fig 4.7. Also in Chapter 4.5 we show how it is possible to distinguish between multiple devices even when the traffic is inconsistent to fully confirm our 2nd assumption and demonstrate the validity of our 3rd assumption.

4.3.2 Feature Extraction

Upon looking at the WiFi data Fig. 4.8, we see a clear need to perform filtering. In the following section we describe the steps taken.

- Data preparation

  To be able to apply machine learning to our datasets, we synchronised the different datasets and did pre-classification on the commercial smart plug data set. For the residential data sets we defined the wattage power of each of the 8 and 10 commercial smart plugs as the input and the ground truth data as the desired output. Since the commercial smart plug data sets were discrete, we matched the ground truth data simply by comparing timestamps. Using a "randomForest" library in R programing framework, we randomly selected 70% of the data set to train the classifier, after which we would use the classifier to predict the number of people in the room using the whole data set. Two different classifiers were constructed this way, using only the data set from the specific measuring environment. The final output of the residential commercial smart plug set and the ground truth self-report was a

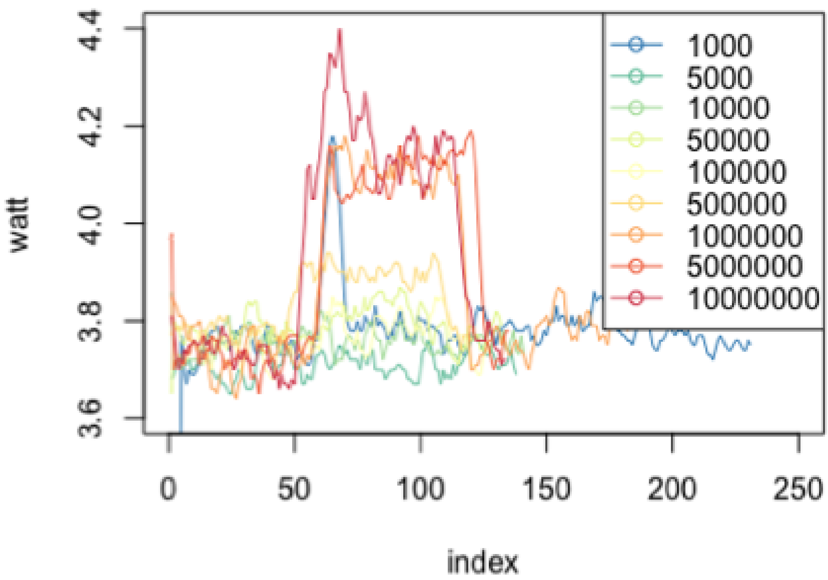


Fig. 4.2 Breakdown between multiple levels of power consumption

data sheet which contained a time stamp, predicted number of people by commercial smart plug and the ground truth value. For the office environments, we used a much simpler approach where, if a commercial smart plugs wattage value was higher than its median average, we would count that a person was present at their desk. A median average was used due to the fact that some desks even without any electric load connected to a smart plug would sometimes register a value between 0 and 1 watt. The ground truth data was extracted from the camera footage taken using computer vision. To make sure that the values were accurate, the values were also manually verified by the authors to remove all the errors. The ground truth data and the commercial smart plug data were synchronised and extrapolated one on to the other. Same as with the residential data, the final output was a data sheet which contained a timestamp, number of people counted by the number of active smart plugs and the ground truth value. The data sheets were slightly modified to make a distinction between presence and occupancy. In this work we define occupancy as the exact number of people in a room, while we refer to presence as a Boolean value describing whether or not anyone was present in a room. Two more columns were

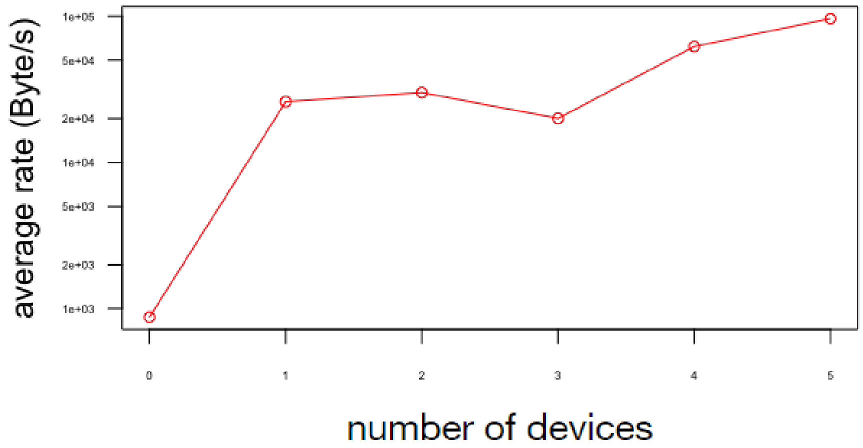


Fig. 4.3 Function representing the correlation between number of devices and power consumption

created to represent the ground truth presence value and presence value induced from the commercial smart plugs by converting all non-zero occupancy values to one. Finally we would like to note that our use of commercial smart plug is to provide a simple benchmark for comparing and showing potential synergy. The optimal method of using smart plugs measuring plug-in load together with a WiFi router's power monitoring in order to facilitate occupancy detection would be outside of the scope of this research.

- Rolling average filter and feature generation

  In the last step, we combined the gathered WiFi routers data with the data from the aforementioned data sheets. The product was a data sheet containing WiFi router's voltage, current, wattage and the last 4 columns containing the smart plug estimated occupancy and presence as well as the ground truth occupancy and presence. What we did next was to use a filter to smoothen out and flatten the data, similar to applying a low pass filter as shown in Fig. 4.9. We start by taking 120 samples from the start of the data set, which represent 1 minute of data gathering due the 0.5Hz sampling period of the WiFi router monitoring. Next, we calculate multiple values from the data frame, such as minimum, maximum, mean, etc. and assign them to the 120th row of the table. We then shift the frame by 1 sample, including all samples from the 2nd to the 121st, writing the results in the 121st row, and

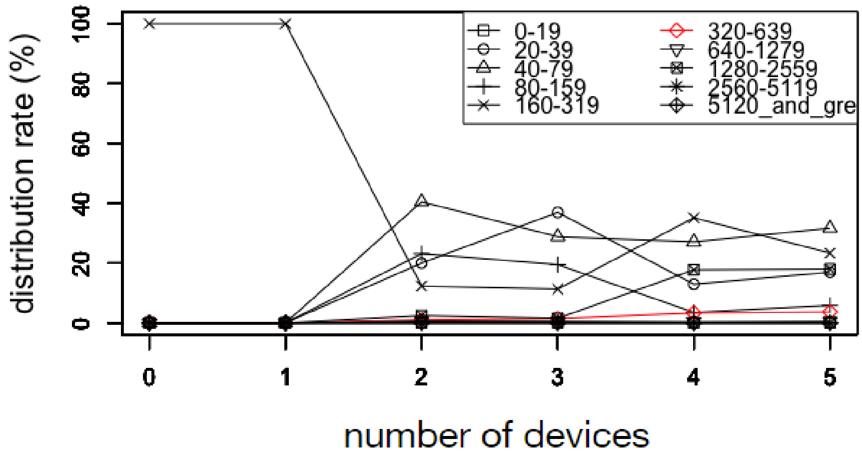


Fig. 4.4 Ratio of messages length 320-639 compared to total traffic

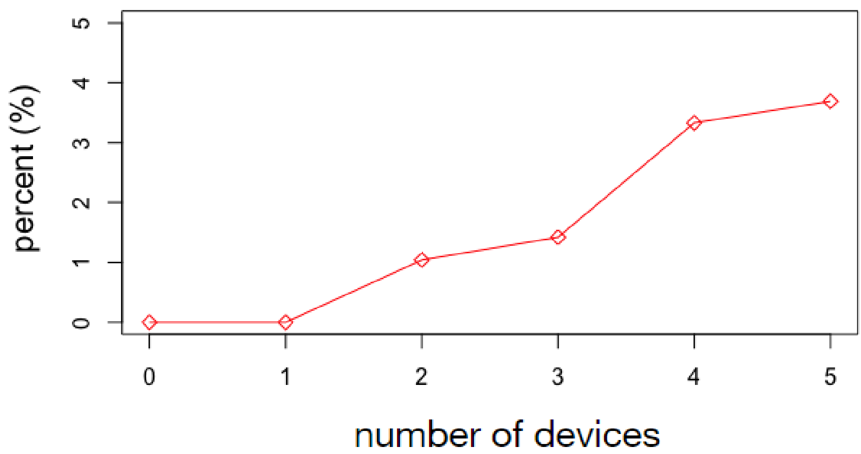


Fig. 4.5 Percentage of overall control messages with the rising number of devices

repeating the process for the whole table, finally dropping the first 119 consecutive rows. Using this method 21 features are extracted to be used in classification.

This approach provides us with three benefits. First, it simply removes some of the noise from the data due the electrical variability and random events as shown in Fig. 4.10 which is present even in stable electric consumption. Secondly, it turn our time series data set into one which is more discrete, which in turn allows us to create a method

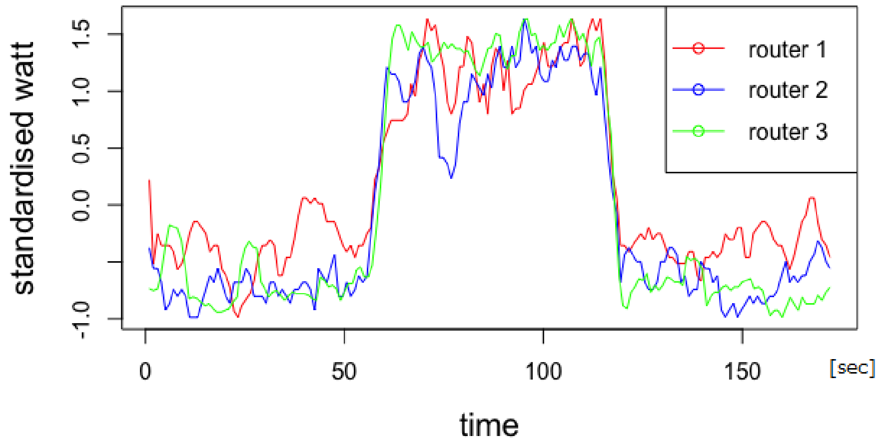


Fig. 4.6 Power consumption of multiple routers when scaled

that could easily process the information stream in soft real time, but on a standard microprocessor. There are several benefits in doing so, since it means that the system would not be dependent on a central data gathering and processing unit, reducing cost and complexity, while improving privacy. Thirdly and most importantly, it spreads out the impact of user actions over a longer period of time. We tested out different length frames and found out that a 1 minute frame can improves accuracy. In Fig. 4.11 we show that the improvement is logarithmic.

The final results of feature extraction can be seen in Fig. 4.12 and Fig. 4.13.

Office WiFi based presence detection classification accuracy was improved from 45% to 90%, and even the residential smart plug classification accuracy from the previous chapter is improved from 40% to 70% for presence and from 30% to 60% for occupancy. The reasoning for this is that, by spreading the impact of each measurement over a 1 minute period, the highly dynamic nature of the WiFi traffic gets distributed, meaning that short periods of inactivity will not be classified as false negatives. In addition, the prefiltering is able to both nullify the effects of low bandwidth period traffic from non-user sources as well as short burst traffic on classification accuracy. Periodic low bandwidth traffic (ex. from smart plugs which were used in the experiment or other such automated sensor devices) is incorporated into the baseline since the filter looks at samples from an interval of time and also scales the values. Additionally, such periodic behaviour can be learned and incorporated similar to oscillations of the power line. Burst traffic on the other hand is

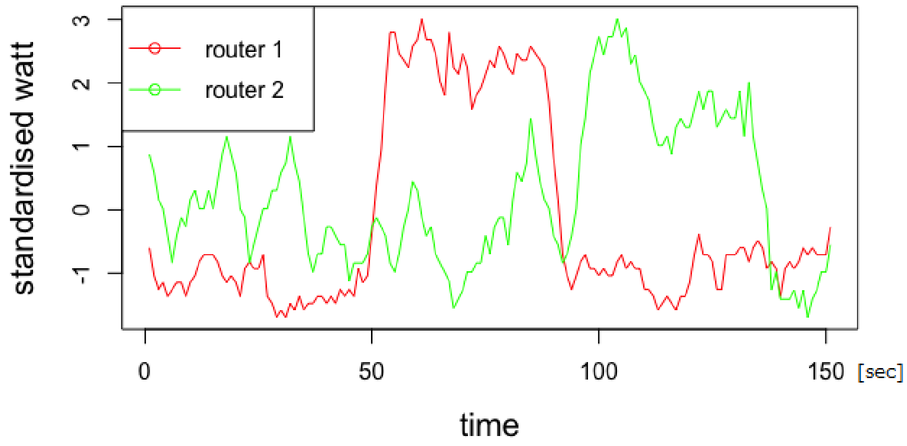


Fig. 4.7 Power consumption of two routers when the traffic is shifted from router 1 to router 2

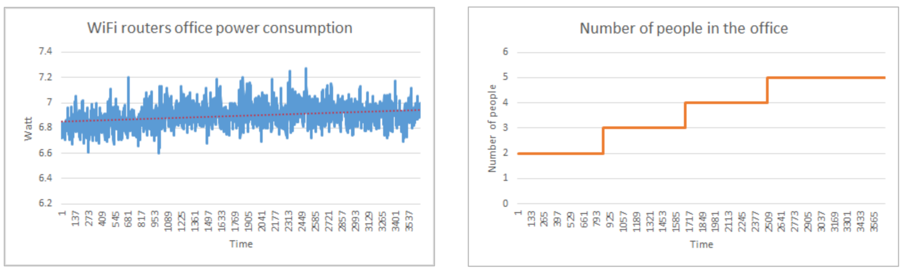


Fig. 4.8 Comparison of WiFi power consumption and the number of people in the room in the same time period

handles by the filter length. Since multiple feature are extracted like minimum, maximum, mean and variability, any spikes which may come from hardware (router models with hard disks) or device behavior (smart device updates) can be nullified due to the values of the other feature. As long as the frame length is sufficiently long, the majority of anomalies can be mitigated.

4.4 Data Gathering

In this section we briefly describe the hardware used in the experiment and the environments in which we gathered the data. Fig. 4.11 shows the how the experiment setup

1.16	1.17	1.16	1.21	1.23	1.18	1.17	1.16

Max	1.17	1.21	1.23	1.23	1.23	1.18
Avg	1.16	1.18	1.20	1.21	1.19	1.17
Min	1.16	1.16	1.16	1.18	1.17	1.16

Fig. 4.9 Example of short aggregate prefiltering

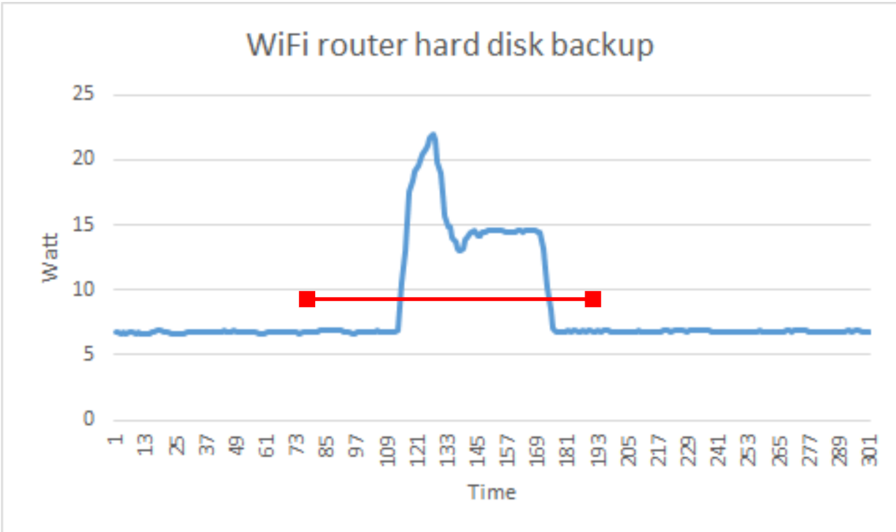


Fig. 4.10 Filtering of random events due to filter length

used to carry out the experiments.

- Commercial Smart Plugs

  Due to increasing improvements in sensing and wireless technology over the last few years, as well as consumer demand, smart metering devices are becoming more and more pervasive. Smart plugs are a type of smart metering device which monitors the electric power consumption of a single plugged in device, usually into a wall socket, instead of the aggregated power consumption of a whole apartment or building. They use wireless communication to transmit their data to a router or an access point and tend to be an order of magnitude cheaper compared to aggregate smart meters. Also, similar to smart meters they are able to monitor and record electrical power properties such as: voltage, current, wattage, phase, etc., but tend to be less precise due to a lower sampling frequencies, which are usually on the scale of

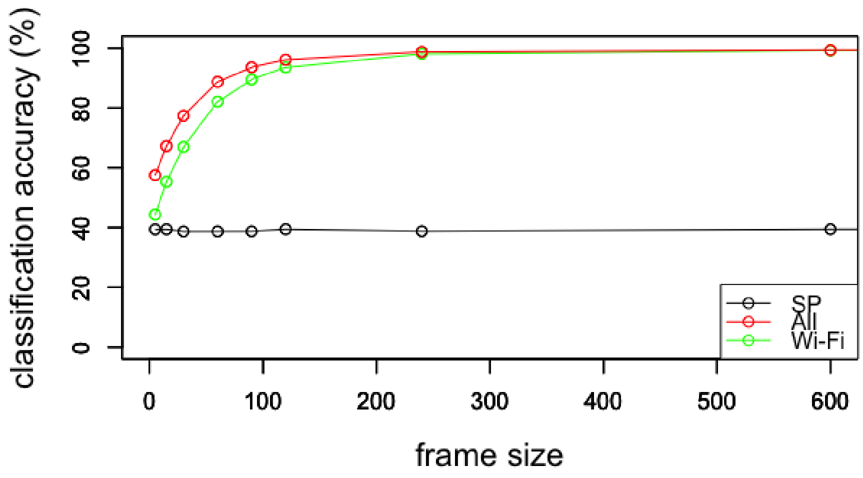


Fig. 4.11 Accuracy improvement based on frame length

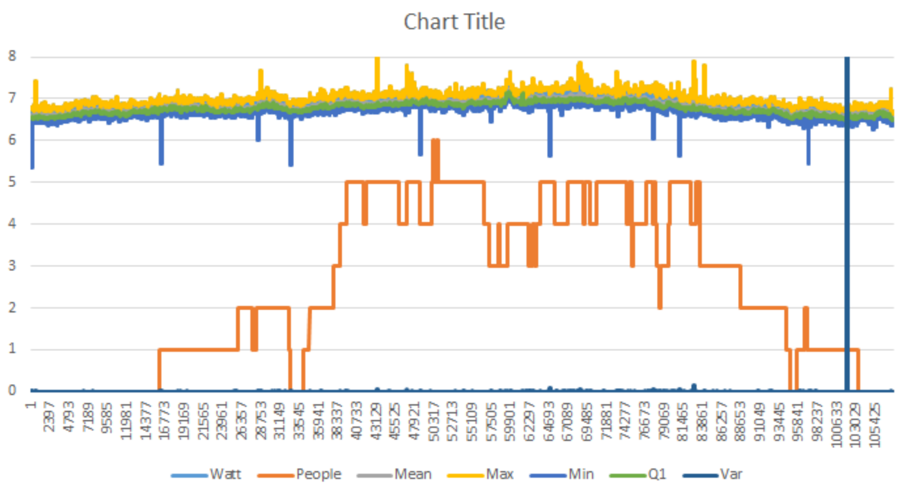


Fig. 4.12 Feature extraction from 1 worth of WiFi data

0.1Hz to 10Hz. Since most users typically only want to know how much a device is consuming in a given moment or over a period of couple of days to a month, their sampling periods are locked to even longer periods, despite the fact that chips are capable of working at a higher frequency.

- Arduino Based Smart Plug

  Due to the stated sampling period limitations, we decided to build our own smart plug. We used an Arduino microcontroller to which we connected a general purpose

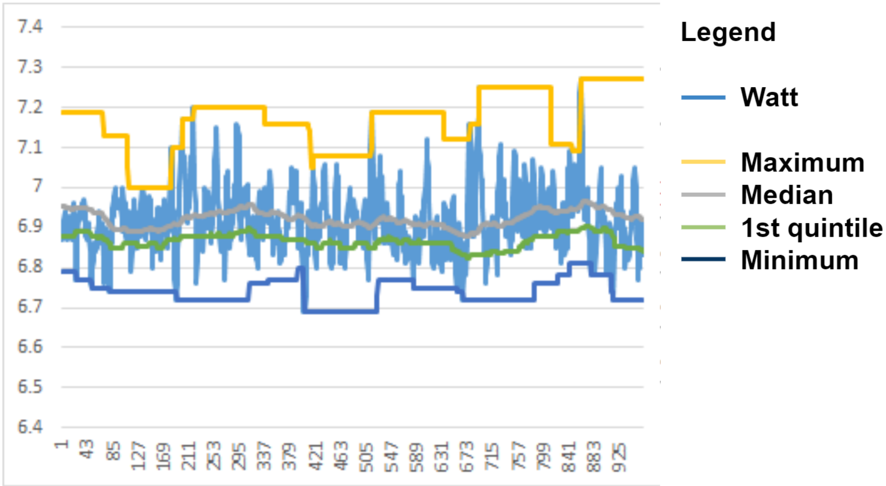


Fig. 4.13 Feature extraction from 1 hours of WiFi data

AC current sensor clamp (CTL-6-P-H series) and a power transformer (HT-605 series) as shown in Fig. 1. It was optimised for loads of up to 5 Amperes and was compared with two other commercial wattmeters and each component was tested with an oscilloscope. There were no significant observable differences between our design and the commercial wattmeters. Next, we set the sampling periods to 0.5Hz (twice per second) and recorded the electrical signal. In electric load classification, a higher sampling frequency is proportional to increased classification accuracy, and some papers have even shown that very high sampling frequencies of several kHz can even achieve real time classification. Our decision to have a sampling periods of only 0.5Hz was based on the fact that we wanted to keep our design as close to the specifications of the commercial ones as possible. By doing so, we would not increase the price by requiring a stronger chip, all the while keeping the smart plug's amount of network traffic down, which might be beneficial in some situations. Also, we would like to note that we used an SD card to record all the information from our smart plug simply due to convenience. Lastly, as we describe in later section, a higher sampling period might not provide a higher benefit due to the application of the rolling average filter on the dataset.

We have conducted measurements on 4 locations, for a period of 1 month each, during the period from late winter to early summer. We have labelled them as following: Residential-single, Residential-family, Office-full access, Office-limited access. Each environment was monitored in 3 ways. First, it had its WiFi router(s) monitored by the smart plug that we had designed at the sampling period of 0.5 seconds. Second, we installed a number of commercial smart plugs to monitor the power consumption of different appliances as a benchmark to compare to and as a way to compliment the WiFi monitoring. The sampling period of the commercial smart plugs was 90 seconds due to the internal buffer limitations. We used a hacked version of a popular smart plug which unfortunately can become unstable when receiving frequent queries. Lastly, our ground truth measurement were created either by using installed video cameras or by using an attendance sheet.

4.4.1 Residential Environment

- Residential-single

  Is a 1-person studio apartment with one router. One custom smart plug and 8 commercial smart plugs were deployed monitoring electric loads (USB charging port, television, laptop, smartphone charger, electric oven, table lamp, refrigerator and hairdryer). Ground truth was determined by self-reporting and the authors believe that the records were accurate within 5 minutes of the written times. During the one month period, there were only 2 days when there were two people in the apartment. During the rest of the time the subject left their home in the morning and came back in the evening.

- Residential-family

  Is a 2-person 35 meter square apartment with one router. One custom smart plug and 10 commercial smart plugs were deployed monitoring electric loads (air-conditioning unit, refrigerator, hairdryer, microwave, laptop, smartphone charger, rice cooker, small speakers, electric toothbrush, and electric toaster oven). Ground truth was determined by self-reporting and the authors believe that the records were accurate within 5 minutes of the written times. For most of the 30 days two people were present at home from evening to morning hours, while leaving and arriving at different times.

4.4.2 Office Environment

- Office-full access

Is a 3-room office environment with 2 networks and 3 routers as shown in Fig. 4.15. Three custom smart plug and 19 commercial smart plugs were deployed monitoring the total power consumption of a working desk (The smart plug was located at the end of the power extension cable). The ground truth was determined from the images taken every 15 minutes from 7 cameras which were positioned to watch over all three rooms. All subjects coming to the office could easily connect all their devices (smartphones, pads, laptops) to either of the networks. Peak occupancy was 16, but average occupancy was 5. Afternoon hours experience larger numbers of people compared to other times which do not seem to follow any rules. Subjects were observed primarily doing work at their computers with breaks, meeting and other activities.

- Office-limited access

  Is a 2-room office environment with 1 router. 1 custom smart plug and 20 commercial smart plugs were deployed monitoring the total power consumption of a working desk (The smart plug was located at the end of the power extension cable). The ground truth was determined from the images taken every 1 minute from 1 camera that was positioned to watch over the main room, while the next door meeting room was not observed. All subjects coming to the office could only connect their working computers to the single networks. This was enforced by whitelisting only allowed MAC addresses. Peak occupancy was 19, but average occupancy was 8. Working hours were generally from 7 in the morning until 11 in the evening. Subjects were observed doing primarily work at their computers with many situations of people falling asleep at their desks or doing work not related to their computer.

Lastly, there were two more observations which we would like to note. First, ground truth data (real occupancy data) shows that weekday and weekend behaviours in our data sets are much more similar to each other than what other papers reported. Second, there seems to be a very consistent residential behaviour. In almost all of our cases, residential subjects left and entered their homes only once. We speculate that this assumption could be further used in all types of residential occupancy detection by focusing on entering and leaving events, regardless of the type of sensing system used.

4.5 Evaluation

In this section we present the classification results and feature relevance in its original form.

4.5.1 Classification Accuracy

To predict room occupancy from a WiFi router's power consumption, we use a random forest classifier library "randomForest" from the statistical programing language R. Our decision is based on scientific literature [60], previous experiences in electric load classification which showed decision trees to gives the best results [53], the implementation potential of decision trees in embedded hardware and, finally, the fact that the number of extracted features is small and they are relatively independent of each other.

We sampled the data both sequentially and randomly. All default setting were kept, except that the number of trees was limited to 10 due to computing restrictions, since a full data set contains over 5.5 million time entries (rows) with 6 to 18 features (columns). The final convergence had a mean square error rate lower than 0.005 for classifiers using all the 21 features and lower than 0.02 for classifiers using 6 features. The variance was still quite high, around 10-20% for 6 feature classification and 0.5-5% for 21 feature classification. The frame features used are: minimum, maximum, mean, median, variability and the first quintile. The classification was carried out twice, first using only the wattage data and afterwards using voltage, current and wattage. The results are as follows: Table 4.3 shows the classification results when using 10%/90% and 20%/80% training/testing data, representing half a week and 1 week of training data respectively. The sequential columns use the first 3/7 days of the data set. "Occupancy" refers to the exact number of people, "presence" refers to whether anyone or no one is present in the room. A "WiFi only occupancy" shows the classification accuracy when only using a WiFi router's power consumption measurements against ground truth occupancy, while a "SP + WiFi presence" shows the classification accuracy from using both the smart plug data and the WiFi router's power consumption measurements against ground truth presence. We used these results to determine if there are any patterns or characteristics to choose the best approach.

Table 4.4 shows the classification results when 70% of the data was randomly sampled for training and 30% was used for testing. This represents 3 weeks of data used for training, with 1 week used for testing. Here we examine what is the best classification accuracy achievable for a model with a long learning time.

Finally we also include Table 4.5 and Table 4.6 show classification accuracy with and without the use of a frame, as well as Fig 4 which shows how accuracy in a office-full access environment is improved by increasing the frame length. A frame length of 1

	Residential-family classification accuracy							
	10/90 sequential		10/90 random		20/80 sequential		20/80 random	
	Watt only	Full	Watt only	Full	Watt only	Full	Watt only	Full
WiFi only occupancy	38.04286	46.26894	43.23219	51.02715	31.21298	37.64087	43.86458	49.58921
WiFi only presence	56.51314	60.3221	60.12465	62.87947	52.15495	54.5551	59.80193	62.25504
SP + WiFi occupancy	42.07687	52.17026	48.2557	57.44598	32.82528	39.55802	44.52964	53.48257
SP + WiFi presence	59.83197	**65.4983**	64.58297	**70.15076**	55.34953	**58.61578**	62.25879	**73.15408**
	Residential-single classification accuracy							
	10/90 sequential		10/90 random		20/80 sequential		20/80 random	
	Watt only	Full	Watt only	Full	Watt only	Full	Watt only	Full
WiFi only occupancy	47.01023	53.91624	43.89635	50.01629	50.57458	61.13812	43.21305	50.84207
WiFi only presence	50.65853	58.96481	59.74997	62.85885	53.50052	64.48393	60.10692	62.87799
SP + WiFi occupancy	64.95408	64.85367	43.9438	52.35128	68.92608	73.57217	48.24685	57.1144
SP + WiFi presence	60.19679	**66.32636**	62.48271	**65.93935**	67.56092	**75.67903**	64.6253	**71.02487**
	Office-limited access classification accuracy							
	10/90 sequential		10/90 random		20/80 sequential		20/80 random	
	Watt only	Full	Watt only	Full	Watt only	Full	Watt only	Full
WiFi only occupancy	55.17801	56.22774	55.16875	57.65774	51.97658	55.16595	52.57016	58.94695
WiFi only presence	70.82195	72.20165	71.07484	71.88571	77.65987	79.84578	82.48888	84.51088
SP + WiFi occupancy	62.97651	63.48659	62.74857	64.01487	57.26485	60.45771	57.88659	66.1221
SP + WiFi presence	76.45572	**78.24647**	77.24451	**77.57451**	82.6674	**85.74783**	88.75841	**89.29583**

Table 4.3 Classification accuracy for short training duration

minute is equivalent to a frame size of 120 samples. Accuracy can further be improved by lengthening the frame at the cost of more time needed to calculate presence and occupancy. In case of the office space, occupancy prediction was increased by 40% percent. If the same approach is used on the commercial smart plug data to extend the influence of events, it is also possible to increase the prediction accuracy of system by 30%.

In Fig. 4.16 we see the classification results of the 93.31% classification accuracy model over a 2 week period. The transitions are clear and the model does not strongly deviated from the ground truth values, since 5.4% of mistakes are offsets by 1 person as shown in Table 4.7. This means that the model can correctly predict the occupancy in a room within 98.7% with a deviation of 1 person.

	70/30 random						
	Residential-family		*Residential-single*		*Office-limited access*		*Office-full access*
	Watt only	Full	Watt only	Full	Watt only	Full	Watt only
WiFi only occupancy	79.83825	99.94377	87.54235	99.97664	93.31138	92.39325	93.49
WiFi only presence	92.27392	99.99178	91.94587	99.99268	99.41259	99.99838	99.34
SP + WiFi occupancy	80.71873	99.95519	89.4036	99.98683	96.51485	95.54691	96.1
SP + WiFi presence	**94.81915**	99.99482	93.71149	99.99465	99.41263	99.99838	99.34

Table 4.4 Classification accuracy for long training duration

Data used to classify	Frame length	Classification accuracy
Desk Smart plug only	no frame	84.76%
WiFi router only	no frame	86.83%
Desk Smart Plug and WiFi router	no frame	87.46%
Router only	1 minute	99.34%
Desk Smart Plug and WiFi router	1minute	99.34%

Table 4.5 Classification accuracy with and without filtering for presence

4.5.2 Generality, Scalability and Cross Validation

Table 4.8 shows the cross validation test in which we used the previously constructed predictive models and tested them with a new data set. Specifically, we used 70% of the data in the residential-family set to training the predictive model after which we used a 100% of the residential-single data set as testing data and vice-versa.

During classification we also looked at which features had the greater significance by applying the R library function "importance()" on the constructed model with results similar to Fig 4.17. Each models input variables we sorted and arranged into Table 4.9 and Table 4.10. The variable in bold represent that a feature had double the impact from the other features. For example in Fig 4.17. we can see that the router 1's minimal wattage (Table 4.9 - Min_Watt_Router1) and router 3's minimal wattage (Table 4.10 - Min_Watt_Router3) have double the importance in the random forest model, off all the other variables.

Data used to classify	Frame length	Classification accuracy
Desk Smart plug only	no frame	39.69%
WiFi router only	no frame	44.54%
Desk Smart Plug and WiFi router	no frame	52.15%
Router only	1 minute	93.49%

Table 4.6 Classification accuracy with and without filtering for occupancy

Classification offset	Percentage rate
1 person	5.37270%
2 person	0.48027%
3 person	0.08877%
4 person	0.01782%
5 person	0.00630%

Table 4.7 Classification offset by number of people

Similar results for feature relevance can also be seen in other test environments. In Fig. 4.18 we can again clearly see that the minimum value plays a much higher importance for occupancy while in Fig. 4.19 all values are equally important for presence.

Our measurements show that it is definitively possible to use a WiFi router's power consumption in order to predict the number of active users present in a room. The accuracy mainly depend on the length of the training, as time is needed to capture user behaviour. This is seen from the slightly inconsistent results for same amounts of randomly sampled

	Cross validation			
	Residential-family (Residential-single as test data)		*Residential-single (Residential-family as test data)*	
	Watt only	*Full*	*Watt only*	*Full*
SP + WiFi occupancy	42.71168	57.3595	28.85432	34.65275
SP + WiFi presence	76.22293	**83.41551**	74.69914	82.57593

Table 4.8 Cross validation

	Feature relevance - Residential							
	Residential-family				*Residential-single*			
	Occupancy		Presence		Occupancy		Presence	
	Watt only	Full	Watt only	Full	Watt only	Full	Watt only	Full
No SP	**Q1_Watt**	**Q1_Watt**	Q1_Watt	**Q1_Watt**	Var_Watt	**Med_Watt**	Q1_Watt	**Mean_Watt**
	Med_Watt	**Med_Watt**	Med_Watt	**Med_Watt**	Q1_Watt	**Q1_Watt**	Var_Watt	Q1_Watt
	Mean_Watt	Max_Volt	Min_Watt	Max_Volt	Mean_Watt	Max_Volt	Med_Watt	Mean_Current
	Var_Watt	Min_Current	Mean_Watt	Mean_Current	Min_Watt	Mean_Current	Mean_Watt	Max_Volt
With SP	**SP.Count**	**SP.Count**	**SP.Presence**	**SP.Presence**	**SP.Count**	**SP.Count**	**SP.Presence**	**SP.Presence**
	Q1_Watt	Max_Volt	Q1_Watt	Max_Volt	Q1_Watt	Q1_Watt	Mean_Watt	Q1_Watt
	Mean_Watt	Mean_Current	Mean_Watt	Ave_Watt	Mean_Watt	Mean_Watt	Max_Watt	Med_Watt
	Med_Watt	Mean_Watt	Med_Watt	Min_Volt	Var_Watt	Med_Watt	Mean_Watt	Max_Volt

Table 4.9 Relevant features for residential monitoring

Feature relevance - Office					
Feature relevance - Office limited access				*Office-full access*	
Occupancy		Presence		Occupancy	Presence
Watt only	Full	Watt only	Full	Watt only	Watt only
Mean_Watt	**Mean_Watt**	**Mean_Watt**	**Max_Volt**	**Min_Watt_Router1**	Mean_Watt_Router2
Min_Watt	Med_Watt	**Max_Watt**	**Q1_Volt**	**Min_Watt_Router3**	Max_Watt_Router2
Var_Watt	Min_Watt	Var_Watt	**Mean_Watt**	Mean_Watt_Router2	Mean_Watt_Router3
Med_Watt	Max_Volt	Med_Watt	Max_Watt	Min_Watt_Router1	Min_Watt_Router1

Table 4.10 Relevant features for office monitoring

data and the fact that accuracy increases with longer training times. Presence, the ability to see if anyone is in the room, is easier to predict than the exact number of people occupying a room. This also become easier as the number of users increases, since there is more training data to improve the occupancy prediction as well as a higher chance of anyone generating traffic. Using more features improves the accuracy of the model and even shows better results in cross verification of up to 83%. Random forest classifiers are generally immune to over-fitting unless a very high ratio of dependent variables to independent variables is present. Since our model has a very small number of variables, we do not believe this to be the case. We discuss other possible limitations in the next section. Looking at feature relevance we find that, in a residential environment, there is little variation since in most cases the number of people present is only 1 or 2, making the Q1 and mean variable dominant. Also, in all cases the commercial smart plug data is more important than the WiFi data which coincides with expected human behaviour. On the other hand when the number of people is increased, maximum wattage becomes more important for presence and minimum wattage becomes more important for occupancy. This experimentally indicates that each additional person can be identified by an increased aggregate power consumption on the router. Additionally, this perfectly fits with the nature of the WiFi protocol. Short WiFi packets have much higher relative power consumption than long packets [85]. Moreover, a higher number of wireless devices would increase the number of beacon signals and probe responses towards the routers, all of which are short messages. Combined, we can confirm our third hypothesis that there is a big enough correlation between the number of people and a WiFi router's power consumption to make our method viable.

4.5.3 Limitations

There are several important points that we would like to address in this section regarding the limitations of our approach, applicability and the need for further testing.

- Generality Despite being able to show high cross validation classification accuracy between residential environments for 2 data sets, there is still uncertainty of the broad generality in the population. The two environments did differ in the number of people, but daily habits and use of technical devices might have been quite similar. While this method assumes that the number of wireless devices will keep increasing in the future and that users will be habitually using these devices, it is quite possible that there might be different population groups with different preferences or user habits. While the authors are confident that this approach is suitable for environments with high device counts, more research will be required to prove the generality of this approach on the general population. This should be achieved either by gathering and measuring more data sets collected from different homes or by a social study of human behaviour.
- Model precision We have shown that regardless of environment a 99.99% accuracy is achievable, but these results are prefaced with long learning times and high susceptibility to environmental change. Specifically, while we are highly confident that the classification algorithm itself is not prone to overfitting due to the characteristics of the random forest, especially when using only the wattage data, there might be modelling bias when using extended feature sets. Electrical signals in the real world are often inconsistent, with our data sets showing that frequency can sometimes

shift by an absolute value of 0.2Hz and voltage has a range of 95.2V to 102.5V. Since changes on the scale of 10 mW can be significant it is hard to say whether or not using more features better removes the noise for the signal or if it adds more bias to the model.

- Real-time limitations Finally, we would like to reiterate that while the WiFi router's power data has a high sampling rate of 0.5Hz, the commercial smart plug data, when combined with the moving average filter, creates a 2 minute delay frame in an office environment and a 5 minute delay frame in a residential environment. So a 92.39325% classification accuracy rate in an office environment means that the classification algorithm will 92% of the time correctly predict the average number of people in the room over the last 2 minutes. Time sensitivity could be increased by improving sampling times and reducing the sliding window frame to shorter period, but from observing user behavior and requirements for power monitoring, we believe that a short delay is fitting since users usually take a few minutes to prepare and leave their space.
- Uncontrollable false positives/negatives For work environments, we are confident from our observations that false negatives do not strongly affect our approach. While ensuring that the camera ground data was correct, we observed people moving in and out of the rooms for meetings, people falling asleep at their desks as well as many different types of other behaviours. These account for a fraction of overall behaviour and add into the 7% error rate (including the misclassification by 1 person). This is mostly around times of transition, when people are moving into and out of the rooms and usually take up to 5 minutes to settle down. The rest of the time behaviour is fairly consistent (people remaining within the range of WiFi) and we are able to correctly classify. While we do not rule out the possibility of false positives, we know that remote access was used, we did not observe any problems. We consider that this is primarily due to the short period of time when the network would be affected by any significant traffic as talked about in the previous section. Home environments suffer much more from false positives, especially when there is only one person in a room. This can be further amplified by cases where people who would not possess (or use) and smartphone, computer or other type of network device. For this reason we couple the approach of using a WiFi router's power consumption together with the power consumption from other devices around the home. Together, they raise the overall accuracy of occupancy monitoring; allow for limited distinguishability of the number of people in a room, all the while not

increasing the complexity of the HEMS from which it is intended, since multiple smart plugs (or smart consents in the future) are required to control wasteful loads in a room.

4.6 Summary

We have shown that by using a WiFi router's power consumption it is possible to achieve up to 92.27% classification accuracy when predicting if anyone is present in a home environment and 93.31% when predicting the exact number of people in an office environment. The method is well suited in a work environment and complementary to other smart plug based occupancy determining methods, especially when a rolling average filter is used which significantly improves classification accuracy.

Fig. 4.14 Measurement system used to gather data

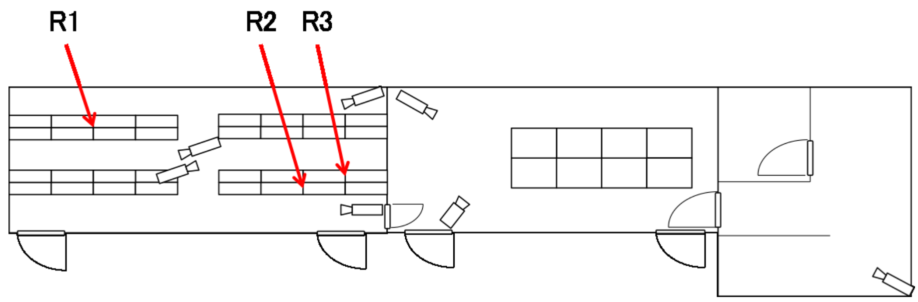


Fig. 4.15 Office layout

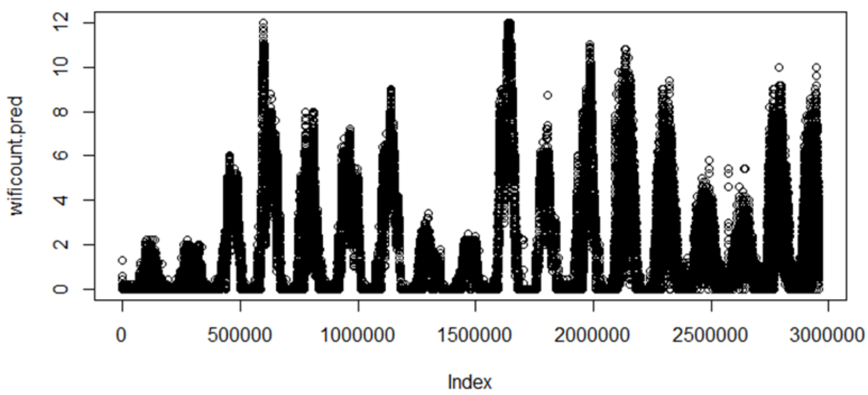


Fig. 4.16 Visual representation of 2 weeks of predictions

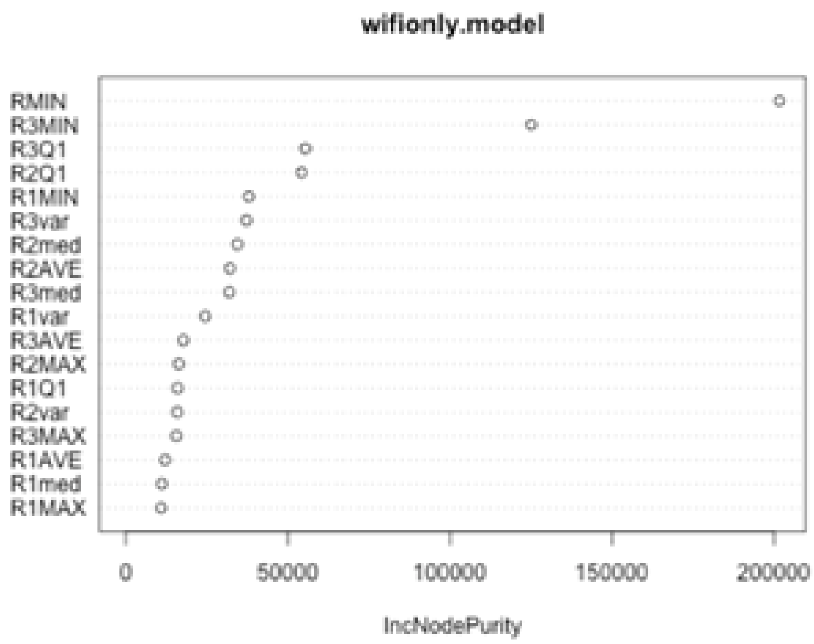


Fig. 4.17 Feature extraction for multiple features on multiple routers

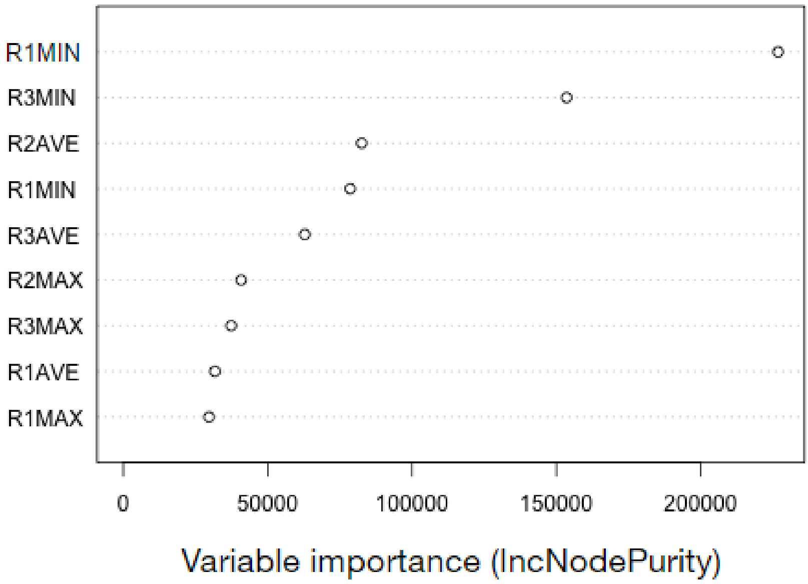


Fig. 4.18 Feature relevance for occupancy

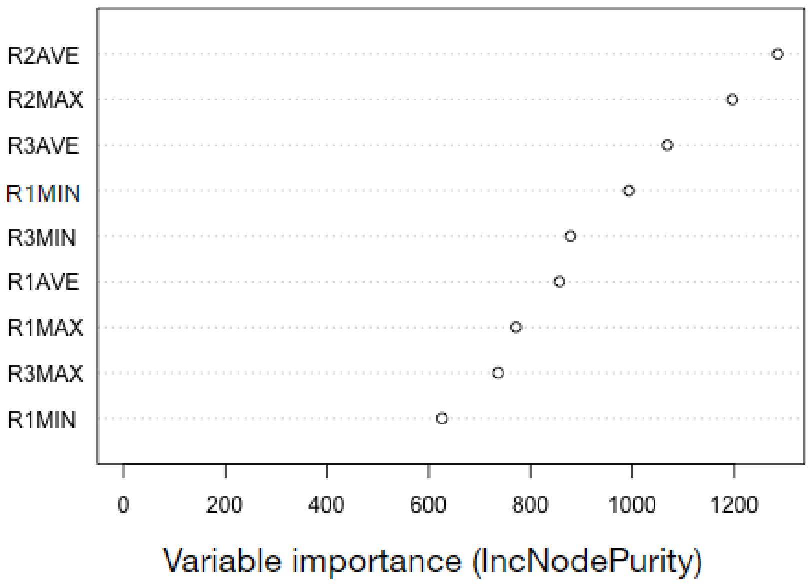


Fig. 4.19 Feature relevance for presence

Chapter 5

Conclusions

5.1 Summary of This Thesis

In this thesis we have addressed residential power management in buildings as a means of reducing electrical waste and lowering peak electrical consumption by using smart plugs. We have analised and tested the usage of a TRIAC element to classify electrical loads as well as conducted multiple test to find a correlation between a WiFi router and room occupancy. In particular, we have proposed:

(1) **An active sensing approach for real-time classification of electrical loads**

We have constructed and tested on over 30 different appliances a new type of smart plug which uses a TRIAC element to modify the incoming voltage as a means to increase data resolution at the output. By doing so we show that it is possible to quickly and easily create a detailed data sets which can be easily used to distinguish appliances.

We extensively tested our approach to insure its safety.We have found that it is possible to subsample the dataset and reduce the sampling time needed to correctly classify without lowering the classification accuracy. An accuracy of 99% is achievable for decision tree types of algorithms, and the light weight of the algorithm allows it to be later implemented embedded systems.

(2) **A short aggregate prefiltering method to extract features used for occupancy monitoring**

A WiFi routers power consumption is proposed as a means of identifying the number of people in a room. Multiple environments are studied and measured from several months to create a data set to confirm our hypothesis. The end results show that there is a strong correlation between a WiFi router power consumption and the number of people occupying a room in home and office environments. We have confirmed by experiment and feature extraction that the correlation is not due to algorithm bias, because of the nature of the random forest, and falls inline with our expectations of how the WiFi protocol operates.

Finally, a novel short aggregate pre filtering method is used and tested which shows that it is possible to greatly improve the accuracy of the classification algorithm by extracting multiple features from a short time frame, in turin spreading user influence and lowering the possibility of false positives/negatives.

In the end by combining these 2 approaches into one smart plug system we are able to provide a product which can be used to retrofit old buildings and be incorporated into new Smart homes to easily control power consumption.

5.2 Future Works

This section suggests research items, which have not been addressed in this research and can be further extended.

（1） **Reducing appliance classification error for rare devices**

Due to the limitations of the data sets for device classification it was not possible to determine if it was possible or not in any ways to extract addition feature which would insure that rare or old devices would still be correctly classified into their appropriate class groups. More research into different type of feature extraction not limited only to the TRIAC method might augment the current approach.

（2） **Increase accuracy in different environments by using user profiling**

While the current system can achieve high accuracy for occupancy monitoring if it is allowed for more time to learn, more research is required to ensure that it is generalisable for any environment. If it were possible to extract additional information such as events which indicate when a person has entered or left the environment it might be possible to further reduce the misclassification error which occurs at transition states.

（3） **Creating a decentralised system**

Lastly and most interestingly, we did not have enough time to study a embedded decentralized approach towards controlling the system. Since both of the proposed methods have been designed to be liteweight from the start, it should be possible to implement both system on embedded hardware. This would allow us to design a decentralised approach which would be more secure and insure a higher level of privacy.

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