University of Dublin

TRINITY COLLEGE

Household Energy Management Using Smart Nanogrids

Padraig Curtin

A thesis submitted to the University of Dublin, Trinity College
in fulfilment of the requirement for the degree of
Master of Computer and Electronic Engineering
University of Dublin, Trinity College

Supervisor: Prof Donal O'Mahony

Submitted to the University of Dublin, Trinity College
May 2015

Declaration

I, Padraig Curtin, declare that the following dissertation, except where otherwise stated, is entirely my own work; that it has not previously been submitted as an exercise for a degree, either in Trinity College Dublin, or in any other University; and that the library may lend or copy it or any part thereof on request.

____

Padraig Curtin
Dated: May 21, 2015

Summary

The electricity grid is currently centrally controlled, balancing supply with demand by predicting loads and attempting to generate power accordingly. It is an impressive system but it has poor demand response capabilities. The system has proven sufficient to meet energy needs until now, but as distributed generation becomes more prevalent it is facing challenges. In light of this there is significant research being done to develop a “smart grid”. A smart grid makes use of advances in communication technology to more tightly couple supply and demand management in the grid, enabling a more distributed approach to grid management. With the right technological developments there are significant monetary and energy savings to be made. Nanogrid systems are one approach to achieve these savings.

A nanogrid is an autonomous entity at the bottom of the grid hierarchy that controls electricity access to local loads. This thesis uses nanogrid hardware prototypes to design and implement a household energy management system. The proposed system consists of a central controller and several nanogrids. The nanogrids each control power access to a major appliance in the household and can choose to supply said power from the grid or from the local renewable power reserves. The choice of what power source to use and when to use it is decided by the controller. The controller communicates via the internet with the grid utility provider to access real time electricity prices. Using these prices, it uses linear optimization to schedule household appliance loads to minimize the electricity expenditure of the user. In addition to load scheduling the controller also optimizes the use of local renewable solar power to further reduce electricity expenditure.

A household energy management system was established and its benefit was examined through simulations. Simulations showed savings of up to 39.5% are possible over the course of a month using the system in place of traditional household energy management; however work remains to improve the systems effect on household peak to average power ratio.

Acknowledgments

I wish to thank Professor Donal O’Mahony for proposing this project, as well as providing supervision and guidance throughout its completion.

I would also like to thank my family; Margaret my mother, Seamus my father and Teresa my sister. Their support has been invaluable

Padraig Curtin
University of Dublin, Trinity College
May2015

Contents

Acknowledgments.......... iv

List of Figures vii

List of Tables viii

Chapter 1: Introduction 1

  Nanogrids and a Bottom-up Approach to Electricity Distribution 1

  Motivation.......... 1

  Report Structure 2

Chapter 2: Background Research.......... 4

  Traditional Electricity Distribution System 4

  Peak to Average Power Ratio (PAR).......... 7

  Demand Response 7

  Electricity Pricing Models.......... 9

    Real Time Pricing (RTP) 11

    Time of Use Pricing (TOU).......... 12

    Critical Peak Pricing (CPP) 13

    Inclined Block Rates (IBR).......... 13

  What is a Nanogrid?.......... 14

  Origin of Nanogrids.......... 15

  Existing Examples.......... 16

  Nanogrid Adoption.......... 19

  Alternative Nanogrid Concepts.......... 20

  Trading Algorithms.......... 22

  Linear Programming.......... 24

Chapter 3: Design.......... 26

  Load Scheduling 27

  Local Renewable Utilization.......... 30

Complete System 31

Chapter 4: Implementation 32
  Hardware 32
    Nanogrid Prototype 32
    Lab Set-up 33
  Software 35
  XMLRPC 35
  TkInter 35
  PuLP 35
  Quick2wire 35
  Rpi 36
  System Behaviour 36
    LoadNanoGrid Class 37
    SourceNanoGrid Class 39

Chapter 5: Simulation Results 41
  Randomised Appliances 41
  Typical Usage Case 45
  Summary of Simulation Results 48

Chapter 7: Conclusion 49
  Possible Future Work 51
    PAR Improvements 51
    Continue Prototype Development 51
    Introduce Local Power Storage 52

References 53
Appendix A- Scheduling Code 58
Appendix B- Local Renewable Utilization Code 59

List of Figures

1. Traditional Grid Components and Connections……………………………………………………….4
2. Grid load fluctuation over a day………………………………………………………………………….5
3. Peak-to Average Ratio……………………………………………………………………………………….7
4. Open ADR 2.0 profile specification…………………………………………………………………......8
5. Determining market scheduling and price……………………………………………………..10
6. Inefficiency of fixed rates…………………………………………………………………………………..12
7. Schematic of generic nanogrid ……………………………………………………………………………14
8. Car as an example of a nanogrid…………………………………………………………………………..16
9. LoCal System Architecture…………………………………………………………………………………17
10. NexTek Power Management System……………………………………………………………………18
11. Electricity market where retailers provide users with RTP…………………………………..23
12. Energy consumption schedules being sent to appliances……………………………………..23
13. Household with multiple appliances and power sources ………………………………………26
14. Complete system controller behaviour…………………………………………………………….31
15. Nanogrid relay diagram…………………………………………………………………………………….32
16. System Dialogue Diagram…………………………………………………………………………………36
17. TkInter load grid graphical user interface…………………………………………………………38
18. TkInter source grid graphical user interface………………………………………………………39
19. Electricity expenditure each day for a month with randomised appliances per day..42
20. Peak-to-average each day for a month with ten randomised appliances per day……43
21. Electricity expenditure each day for a month with typical use case……………………..45
22. Peak-to-average ratio each day for a month with typical use case………………………..46

List of Tables

1. Random appliances monthly figures based on wholesale prices from SEMO…………………..43

2. Non-random appliance schedules……………………………………………………………………………..45

3. Set appliances monthly figures ……………………………………………………………………………….46

Chapter 1: Introduction

Nanogrids and a Bottom-up Approach to Electricity Distribution

The current electricity grid is centrally controlled and for the most part responds to demand by increasing or decreasing generation. This cumbersome approach can lead to wasted resources and unnecessary energy loss .A new concept known as a “Nanogrid” aims to change this. A nanogrid is an autonomous entity that sits at the bottom of the grid hierarchy. It consists of a controller with a load connected to one or more electricity sources. By negotiating with other nanogrids and utilities the controller intelligently matches the load to the most appropriate source of power. This thesis seeks to explore the potential of nanogrids to implement an energy management system at the residential household level.

Motivation

Nanogrids and the related field of the smart grid are a central component of current research in the area of energy conservation. Due to increasing adoption of renewable energy the current centralized model of electricity generation and distribution is becoming outdated and new systems must be developed to take its place. In some countries the switch to a smarter grid has commenced. Italy has a smart meter penetration rate of approximately 85% and other EU countries intend to mandate smart meters in order to unlock estimated savings of €53 Billion [1]. The United Kingdom plans to mandate smart meters to all households by 2020. Ireland, France, Spain, Norway and The Netherlands are also expected to have 100% smart meter installation rates by 2020 and the likelihood is that other member states of the European Union will follow suit. Smart meters will lower retail electricity rates by allowing the adoption of dynamic electricity pricing models such as real time pricing (RTP), critical peak pricing (CPP) and time of use (TOU) pricing. By implementing these pricing models the reliance of the grid on peaking power plants will be reduced. The concepts of the smart grid and dynamic electricity pricing models will be discussed in chapter two.

It’s not only developed nations that stand to benefit from a more distributed approach to energy conservation. Nordman et al [2] compare the benefits of the upcoming smart grid revolution to the benefits of the advancement from landlines to mobile technology. In some developing countries the communication infrastructure skipped the landline stage of development and installed a mobile network which provided a superior service for a fraction of the cost. In the same way there is the potential for a country to bypass the development of an expensive centralized power system with large power plants and a heavy duty distribution system in favour of a distributed system consisting of nanogrids.

Report Structure

Chapter two outlines the background research that was necessary for the completion of this project. This includes definitions and descriptions of various concepts the reader would need to learn to understand the work carried out in this thesis. Information on subjects such as the traditional electricity grid, demand response and electricity pricing models are presented. A literature review of existing work into the field of nanogrids is also presented.

Chapter three outlines the designs of the electricity expenditure reduction systems implemented in this thesis. The first method presented uses linear optimisation to schedule a household’s electrical appliances access to electricity. The second method intelligently assigns access to local renewable energy to appliances when grid electricity is expensive. The two methods are then combined in a complimentary manner to form the completed energy management system.

Chapter four details how the designs from chapter three were implemented. A description of the nanogrid prototype hardware and the labs experimental set-up are given. Details of the software classes created to operate the nanogrid are presented.

Chapter five describes the results of the simulations run to test the efficiency of the systems implemented. Two simulations are run. The first uses randomised data to show the system performs rigorously under a wide range of conditions. The second uses a predefined data set to allow closer inspection of the emergent behaviour of the system.

Chapter six contains a discussion of the results of the simulations described in chapter five.

Chapter seven summarises the conclusions drawn from the results of the thesis and provides suggestions for possible future research.

References are included at the end of the report and all code written is included on a cd inserted in the inside of the back cover. An appendix contains some of the more relevant code snippets produced.

Chapter 2: Background Research

This chapter contains background information required to give the reader some context to understand the work undertaken in this thesis and a literary review of research relating to nano-grids.

Traditional Electricity Distribution System

The purpose of an electrical grid is to allow electricity suppliers deliver their power to consumers in a reliable and economical manner. Traditionally such a system consists of generation stations to produce power, transmission lines to carry high voltage power long distances while minimizing I^2R energy loss and distribution lines to deliver stepped down power into homes and businesses.

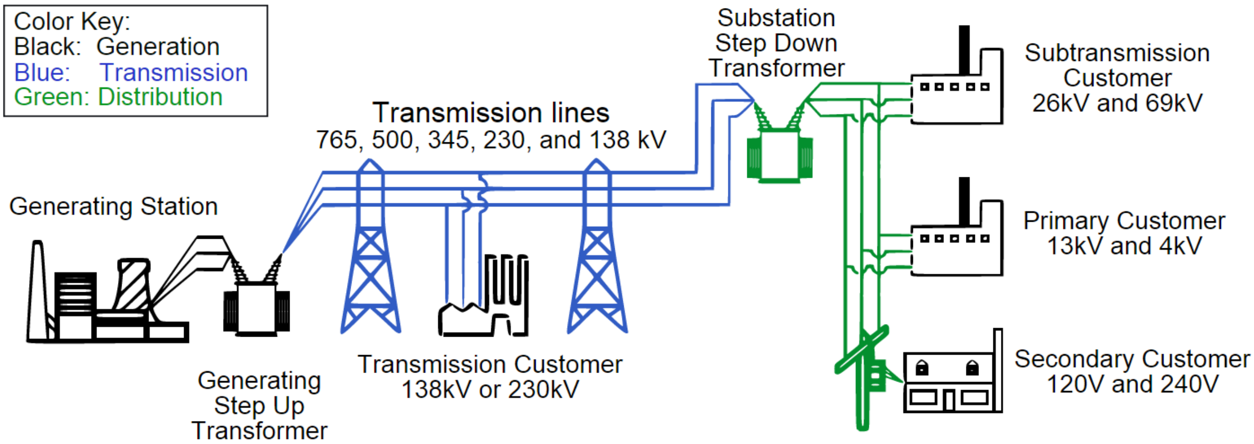


Figure 1: Traditional Grid Components and Connections [3]

In order to keep such a system operating correctly three factors must be monitored and regulated; power, voltage and frequency. The control system used must ensure that supply closely matches demand at all times. It does this by adjusting generation, switches and loads. If insufficient power is produced line voltage and frequency will drop causing issues for the performance of end users machines. If demand exceeds supply by significant amount generation equipment will shut down leading to blackouts.

Adjusting generation at times of high electricity demand is accomplished using peaking plants. Due to the fact that these plants only supply power occasionally (sometimes only a few times a year) their power commands a much higher price on the electricity wholesale markets. Peaking plants are used in conjunction with base plants which supply a consistent minimum amount of power to satisfy demand. Since peaking plants are only intended to run for short periods and building efficient power plants is expensive, peaking plants are generally not as efficient as base plants. Therefore it would be better if these plants never had to be used. This has led to a push towards a new more intelligent grid paradigm called the smart grid.

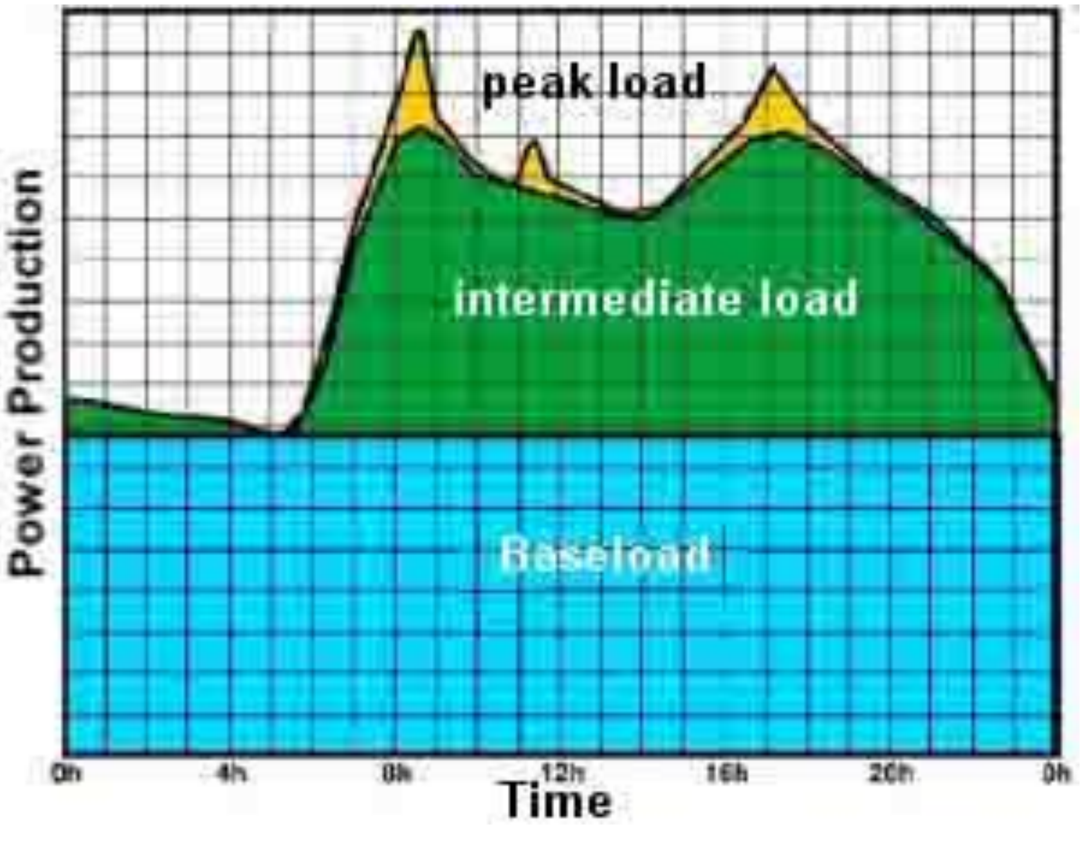


Figure 2: Grid load fluctuation over a day [4].

The smart grid is a modernised version of the grid where information about electricity is collected and processed in an automated fashion to improve the efficiency, reliability and economics of electricity production and distribution. These improvements are made possible by two-way communication technology and computer processing that has been used for decades in other industries. Use has commenced on electricity networks, from power plants and wind farms all the way to the consumers of electricity in homes and businesses [5]. In addition to communications systems, information gathering devices like smart meters can be installed on nodes on the grid. This removes the need to have workers reading meters and identifying dysfunctional equipment easier. The benefits of the smart grid include reducing peak demand and by extension reducing capital expenditure on peaking plants.

In recent years renewable sources have seen an increase in popularity. While they provide benefits to the environment and help prepare society for a future where fossil fuels have been exhausted, they present a challenge to the current control systems that operate the grid. Traditionally to respond to increases in demand, additional generating capacity is introduced. This might consist of starting up a natural gas power plant. The benefits of a plant of this nature are that it will reliably produce power at the time it's needed and it can be started at relatively short notice. The amount of power produced can be directly controlled by the amount of fuel supplied.

A renewable source, like wind power for example, does not offer these benefits. Wind turbines will only supply power when wind is available so the grid control system has no control over the quantity or timing of power produced in this way. Therefore wind power cannot reliably be used as a lever to control power in a grid. Due to this problem reliable peaking plants, usually powered by gas or petroleum, must be kept on standby to commence energy generation at a moment's notice if the wind supply stops. The need for these back up power stations increases the overheads for wind electricity production and decreases positive impact on the environment.

Peak to Average Power Ratio (PAR)

PAR is a measure of the difference between the peak load of a system and the average load. It's given by (1):

$$PAR = \frac{Peak\ Load}{Average\ Load} \tag{1}$$

In the grid it is beneficial to avoid spikes in demand to avoid having to use peaking plant generation. This keeps down the price of generation which is in the interest of the distributor. They will also pass on savings to the consumer. Therefore having a low PAR value in a household is of benefit to the energy provider and ultimately, the consumer. A PAR value of one indicates there are no peaks in a data series.

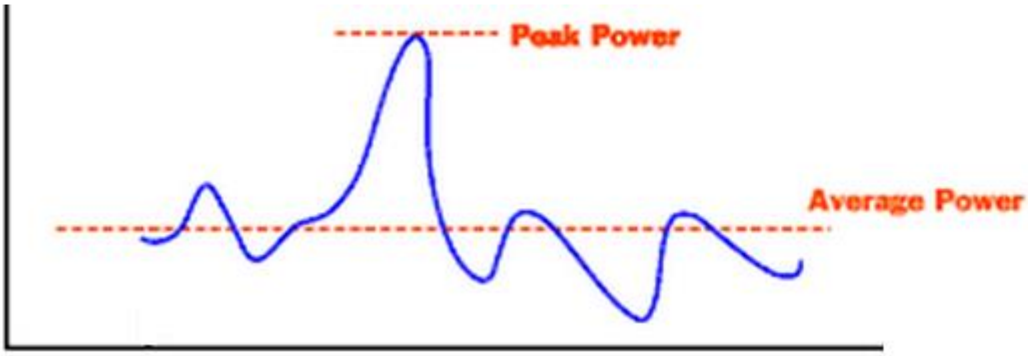


Figure 3: Peak-to Average Ratio

Demand Response

One answer to the problems of introducing renewable energy to the grid and reducing PAR is demand response (DR). DR is "a set of activities that reduce or shift electricity used to improve electric grid reliability, manage electricity costs, and provide systems that encourage load shifting or shedding during times when the electric grid is near its capacity or electricity prices are high" [6]. It is seen as a key strategy for grid and market reliability [7]. There are various different approaches currently taken for DR. Manual response involves an email or telephone call from an electricity supplier informing a participating consumer that they must reduce their load. The consumer must then manually turn off or alter comfort set points on equipment. This is known as load shedding. Semi-automated response involves pre-programmed responses on the consumer’s end which are triggered by a person with a centralised control system at the electricity provider. Human intervention is not required in fully automated demand response. In fully automated demand response systems it is important that a home or business owner is able to over-ride the automated decisions if a reduction in end use service would not be acceptable. Current efforts to create a standard for automated response called open automated demand response (OpenADR) are being led by North American companies and researchers. The OpenADR Alliance has formed to aid development and adoption of smart meter standards in the energy industry [8]. OpenADR 2.0, their current standard, is illustrated in figure 4. It uses the definitions of Virtual Top Nodes (VTNs) and Virtual End Nodes (VENs). In interactions between nodes one node is designated a VTN while the rest are VENs. Communication only occurs between VTNs and VENS. There is no peer-to-peer communication in this standard.

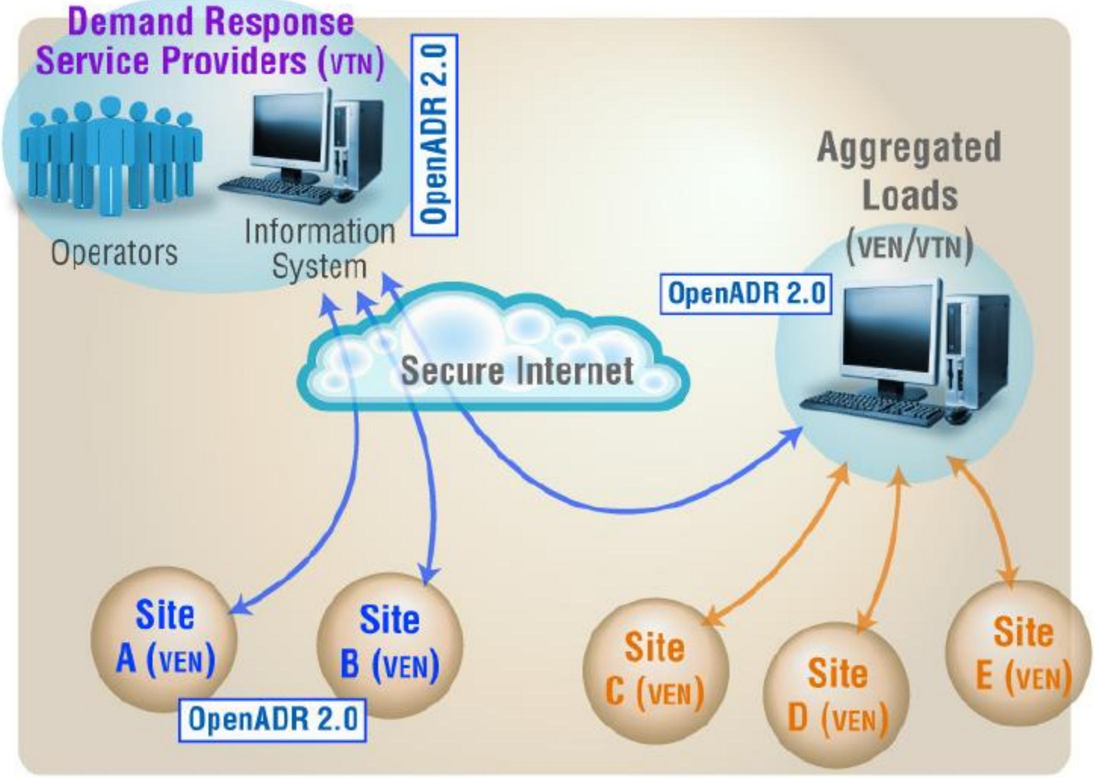


Figure 4: OpenADR 2.0 profile specification [8]

Vardakas et al [9] provide an extensive survey of DR schemes. They classify them into control mechanisms and incentives for user adoption. Control mechanisms can either be centralised or distributed. In a centralised system the customer communicates only with the utility whereas in a distributed system they also communicate with each other. This distributed communication can provide the utility with valuable information about total consumption [10]. A second category of DR schemes are categorised according to consumer incentives offered. These are covered in the electricity pricing models section later in this chapter.

Electricity Pricing Models

The wholesale price of electricity fluctuates with time. This fluctuation is due to the different costs of competing generators between times of high and low demand. The price changes day-to-day and over the course of each day. Electricity is generally most expensive in the evening and cheapest in the middle of the night. Wholesale prices for the Irish market can be found at the Single Electricity Market (SEM) website [11].

To participate in the market wholesalers and retailers must comply with the SEM code. The code specifies that each market operator must be represented by a data processing entity which will maintain a communication interface to the market at all times. The prices for electricity are calculated using Market Scheduling and Price (MSP) software. Each energy producer has a minimum price they are willing to accept for power based on the cost of production. The MSP software calculates a set of day ahead prices by predicting demand. These prices are used as signals by energy producers informing them when they must be ready to supply power to the grid. This is necessary as it takes time to start up some generators. The scheduler uses cheap energy sources first. When it runs out of generating capacity at the lowest price point it will increase the price and schedule more expensive power sources. It will keep increasing the price until it has enough energy scheduled to meet projected demand. Thus, electricity price is dictated by the most expensive power source needed.

This price is just a guideline as actual use will rarely exactly match predicted use. To reflect this the actual price paid is calculated ex-post i.e. after the fact. This is known as the System Marginal Price (SMP) and is calculated using a shadow price based on actual energy used combined with an uplift price. Uplift is an extra payment added on to compensate producers who incurred extra costs due to the difference between forecasted demand and actual demand. This is to cover start up and no load costs.

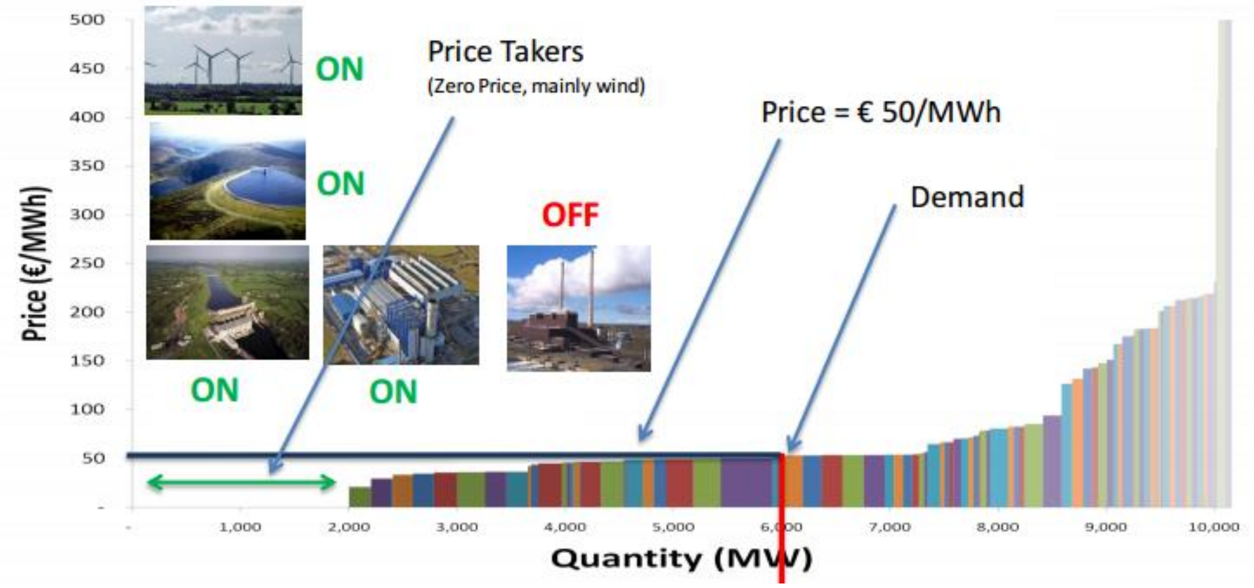


Figure 5: Determining market scheduling and price [12]

Although electricity retailers are getting electricity at different prices at different times, most consumers pay an average rate regardless of when they use power. In order to incentivise demand response various time-differentiated alternative pricing models have been proposed.

Real Time Pricing (RTP)

In an RTP model utilities provide their customers with efficient price signals to manage loads, reduce cost and maximise profitability [13]. In this way it is a useful tool for utilities to increase competitiveness and increase their customer base. In practice, adoption of RTP is limited. The complexities and risks associated with the roll out of the technology makes utilities wary.

Different prices are offered to customers depending on the time of day. The prices are set by predicting demand for electricity in the grid. These predictions can be made days, weeks or even months ahead of time. Dynamic pricing is then used to respond to events and give a more accurate price in near-real time. If the utility predicts there will be a surge in demand they can broadcast an increased price for that time slot. To save money customers will be incentivised to move their loads to a less busy time, lowering the overall PAR of the grid.

One problem to be overcome is the issue of targeting customers. An appropriate target audience must be identified and the pricing structure must be designed so that supplying these customers does not result in the utility losing money. The customers would have to be willing to respond to price signals in an appropriate manner. From the utilities point of view the most appropriate customers would have high demand coincident with system wide peaks. If this is not the case then the utility is merely transferring money to the customer without receiving any increased benefit in terms of system load balancing. From a customer's point of view there are three factors to be considered before signing up for RTP:

1. The risk/reward structure being offered.
2. The availability of other pricing options.
3. The calculation of baseline load.

Price volatility varies based on how far ahead price signals are provided. Customers vary in their willingness to absorb the risk associated with this. They desire a high degree of forecasting and monitoring data to minimise this risk.

Time of Use Pricing (TOU)

A TOU model is similar to RTP in so far as the price a customer pays varies over the course of the day. However the prices are set well in advance and do not adjust to reflect actual conditions [14].

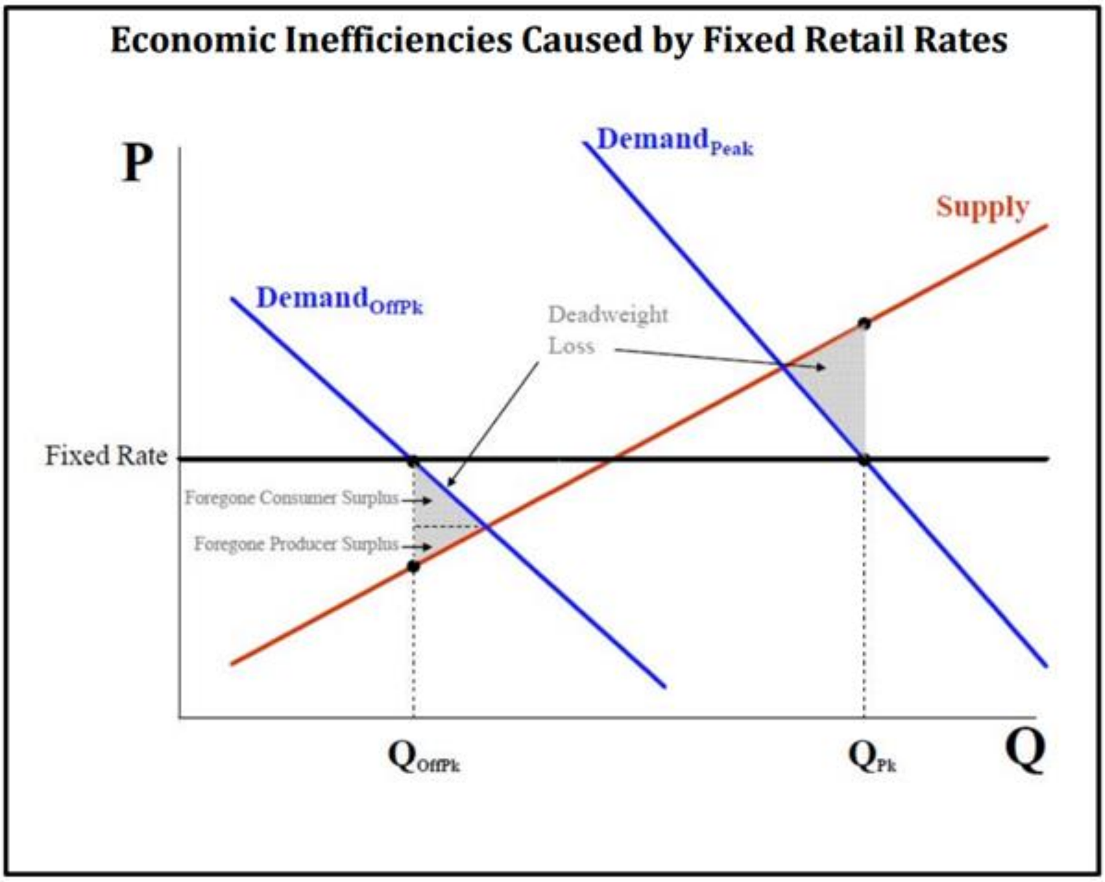


Figure 6: Inefficiency of fixed rates [14].

Figure 6 shows peak and off-peak conditions with a fixed rate. At off-peak times the rate is too high and too little electricity is consumed. The opposite is true at peak times. The shaded triangles show the efficiency loss when the fixed rate does not represent the TOU price. From the geometry of a triangle it can be seen that any period with exogenous locational marginal price the economic loss of deviation from the TOU price is half the change in quantity times the change in price. TOU does not provide as accurate a pricing signal about the value of power at a location as RTP but it can provide a better representation of value if a pricing approximation such as critical peak is used.

Critical Peak Pricing (CPP)

CPP augments a TOU model by introducing a high or “critical” price during times of system stress [15]. RTP closely tracks time dependent wholesale electricity prices and has been implemented successfully with large industrial power consumers. However, most policy makers consider hourly RTP to be too complex for small electricity consumers as it would expose residential customers to volatile wholesale electricity markets. CPP is considered a reasonable alternative where dynamic prices are being considered but RTP is deemed inappropriate.

CPP uses a TOU tariff structure where an increased price can be put into effect on a limited number of days per year to coincide with events that cause surges in power usage such as heat waves. Customers are generally warned a day in advance that a high price day is being implemented. Customers can be provided with automated control technology in some cases to help support efficient load drop.CPP is not considered as economically efficient as RTP but it does have the benefit of diminishing the price risk for the consumer inherent to the market based RTP model.

Inclined Block Rates (IBR)

IBR is an incentive for customers to reduce their load in the long term and keep below a set load threshold. With IBR the marginal price increases by the total quantity consumed [16]. When the consumer’s residential load reaches a defined threshold an increased price will come into effect. This incentivises users to balance their loads to avoid paying higher electricity bills thus improving their PAR [17]. IBR has been widely adopted into the pricing tariff models of utility companies. For example, the Southern California Edison Company has a two level residential rate structure where the price of the second level is 80% higher than the first level.

What is a Nanogrid?

The concept of a nanogrid is relatively new and does not have a universally accepted definition. Nordman et al [2] define it as "a single domain for voltage, quality, reliability, price, and administration. It must have at least one load or sink of power—which could be electricity storage—and at least one gateway to the outside." Nanogrids manage loads locally to decrease energy usage and if combined with energy price incentives they can lower energy costs. A schematic of a generic nanogrid is shown in figure 7.

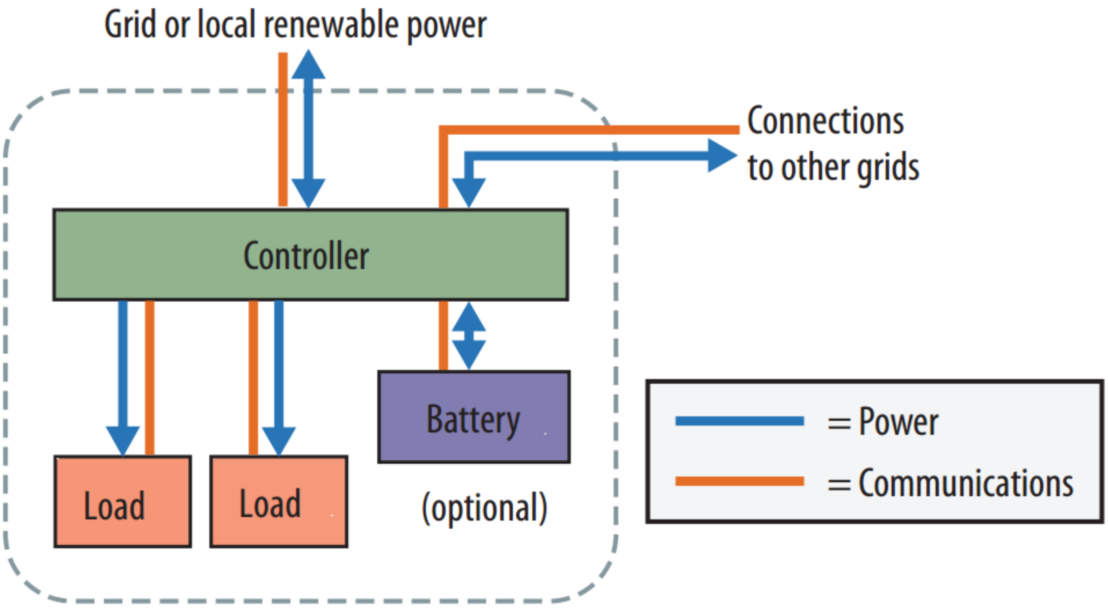


Figure 7: Schematic of generic nanogrid [2]

Communications accompany power flows in a nanogrid. The controller manages access to electricity for loads based on information it receives from energy suppliers. Energy suppliers can include other nanogrids if they have electricity storage capability. One advantage of this system is the option to buy energy when it is cheap, for example in the middle of the night, and use or sell it to other nanogrids at times when high demand for electricity increases its price. Nordman et al [2] consider batteries an optional feature for a nanogrid. The use of nanogrids allows novel methods of power distribution that would not have been possible previously such as choosing between two power sources based on the prices on offer from each source.

Nanogrids consist of a controller, loads, storage (optional) and gateways [18]. Loads are electrical devices that request power through the nanogrid. The controller provides or denies this power by negotiating with other grids. If a deal is successfully negotiated the controller will activate a relay to allow power flow to the load through a gateway. A gate way is a power exchange and communication interface between two grids. The nanogrid does not know what is on the other side of a gateway. The only information it gets from the communications are the basic price of the power being negotiated, the power capacity of the gateway and the amount of power available.

Origin of Nanogrids

The macrogrid is a system that provides reliability with little direct coordination between loads and sources. Balancing is achieved by predictability of loads in the absence of sharp increases in demand. As grid sizes decrease the need for coordination mechanisms between supply and demand increases. Historically the cost of such technology was prohibitively expensive, but that is no longer the case.

A microgrid is a small-scale power grid that can operate independently or in conjunction with the area's main electrical grid. Microgrids provide many benefits which make them attractive. They can provide better local renewable energy and storage integration than the macrogrid [19] and they can provide a variety of voltages, both AC and DC [20]. Microgrids can offer both environmental and economic benefits but their adoption has been hampered as the market size has been too small for industry standards to develop.

Nanogrids address fewer problems than microgrids but have much greater application potential; thus they enable the development of standard technologies that can quickly become widespread [18]. Nanogrids are similar to microgrids but they only provide a single voltage level and they only have a single internal power distribution entity.

Existing Examples

Universal Serial Bus (USB)

A simple example of a nanogrid is a computer connected to peripheral devices via a USB connection. The USB provides power to devices which are equivalent to loads in the nanogrid paradigm. A powered USB hub becomes its own nanogrid independent of the computer. USB 3.0 can provide up to 4.5W of power to a load.

Power over Ethernet (PoE)

Ethernet cables are also capable of delivering power. As of the IEEE 802.3at-2009 standard Ethernet cables can deliver up to 22.5W of power [21]. PoE is commonly used to provide data and power but it is possible to use it for power alone.

Car Electronic System

Many of the components of a cars electronic system are powered from the 12V ignition battery. Radios, on board entertainment systems and electronic sensors use power from the battery and external devices can gain access to power through the cigarette lighter port. As trends shift towards electric vehicles cars will exhibit another feature of nanogrids; they will be part of the macrogrid when plugged in but will be capable of disconnecting and operating independently of the rest of the grid in an offline mode.

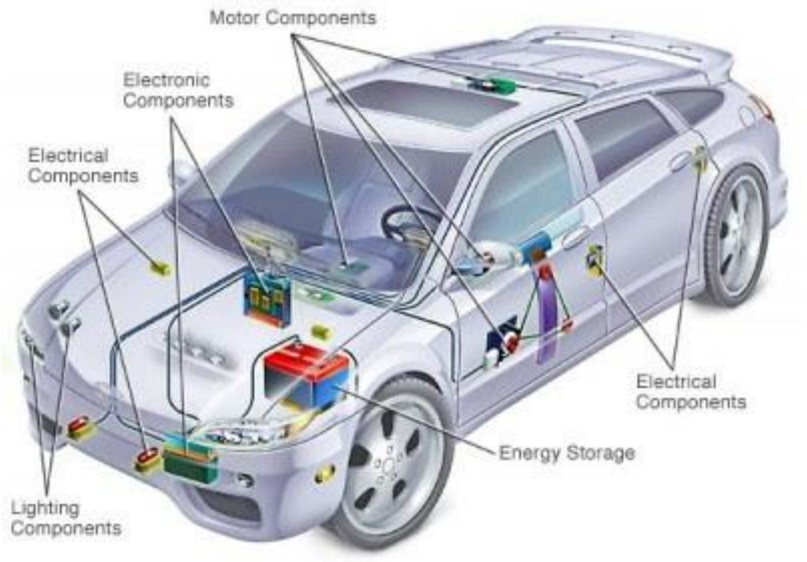


Figure 8: Car as an example of a nanogrid [22].

LoCal System

The LoCal system is an example of a nanogrid proposed by He et al [23]. The system uses an Intelligent Power Switch as its controller, has local storage and allows multiple loads. A LoCal grid can buffer variation in load and generation by using its storage in an intelligent manner. In this way it can present itself as a constant load simplifying its effect on the macrogrid. It can also use it's storage to moderate its energy imports from the grid in response to price signals, adding demand response capability.

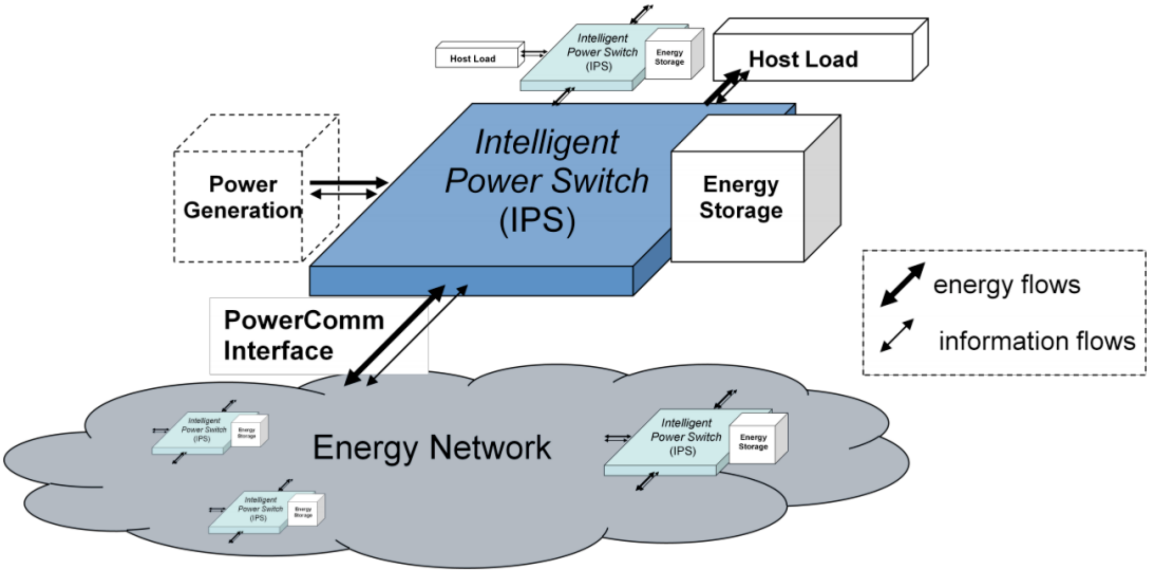


Figure 9: LoCal System Architecture [23]

Emerge Alliance

The Emerge Alliance are developing area specific micrograms that when interconnected create a resilient and versatile building wide or campus-wide energy network [24]. The members of the Alliance have developed compatible products in the following areas:

- Infrastructure- Bus bars, device connectors
- Power- Power supply modules
- Peripherals-Light fixtures, ballasts, drivers
- Controls – Sensors, device controls, gateways, user interfaces

NexTek

NexTek have developed a Power Server Module (PSM) which accepts power from DC renewables, AC grid power and battery backup, converting it to 24DC for household lighting applications [25]. Using input from sensors and controls the PSM decides how to efficiently allocate energy. The system works with both cloud based app controls and traditional light switches. It is designed to integrate into existing building management systems.

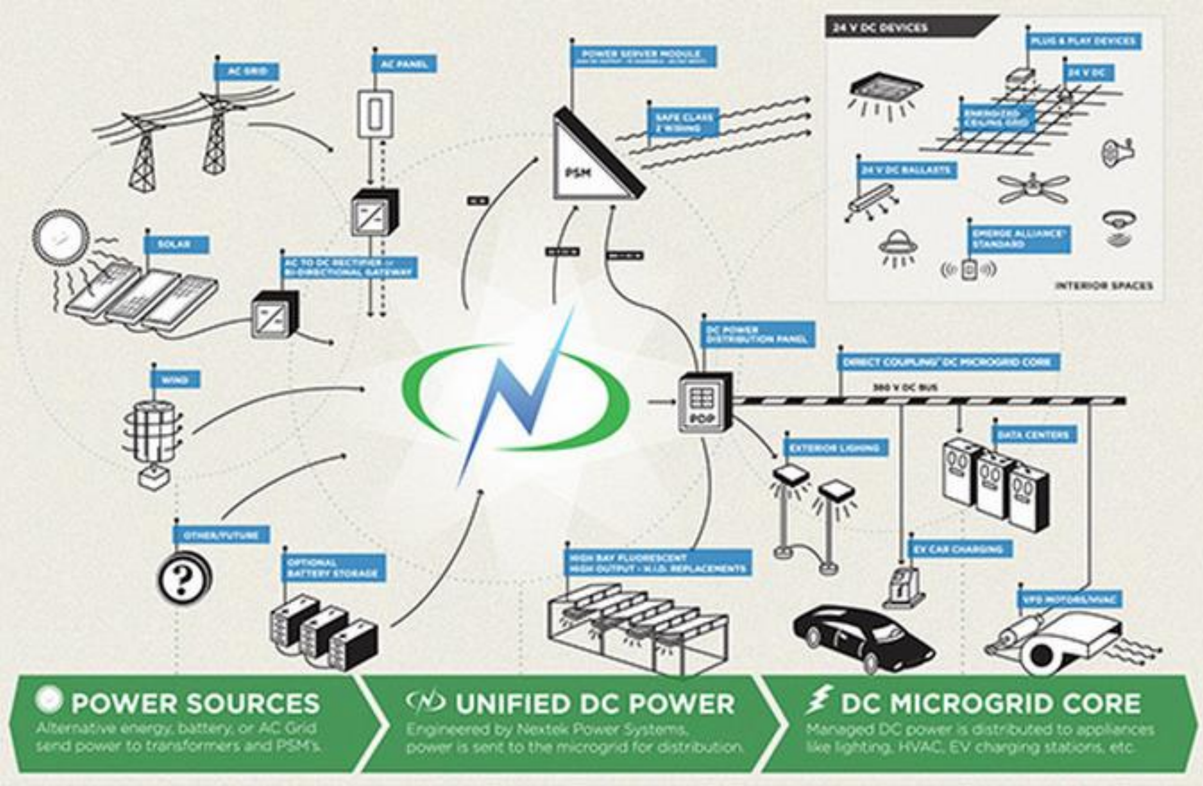


Figure 10: NexTek Power Management System [25].

Developing Nation Households

In locations where households do not have access to grid power 12V batteries are sometimes used to power devices. These are generally charged off-site, by generator or from local renewable energy sources. An example of such a nanogrid would be an off grid household with a battery and a photo voltaic panel. The system can be used to power the household or it could connect to nearby structures such as schools and clinics to offer them power.

Nanogrid Adoption

Nanogrid adoption has been identified as a solution to help electrify rural communities. An Indian village would be declared as electrified by the Ministry of Power if the following definitions are met:

1. Basic infrastructure such as Distribution Transformer and Distribution lines are provided in the inhabited locality as well as the Dalit hamlet where it exists. (For electrification through Non-Conventional Energy Sources a Distribution transformer may not be necessary).

2. Electricity is provided to public places like Schools, Panchayat Office Health Centres, Dispensaries, Community centres, etc.

3. The number of households electrified should be at least 10% of the total number of households in the village.

Mishra et al [26] states that, by this definition, 20% of villages in India lacked access to electricity in 2009. Obstacles to rural electrification include: (a) inadequate grid infrastructure due to geographical locations and widespread distribution of villages; (b) large transmission losses on long distance feeds; (c) overall country wide electricity shortages. Renewable power can be used to solve rural power shortages. If local power supplies are deployed to individual houses or communities these problems can be overcome. This is known as distributed generation and would require nanogrids to operate effectively. Solar power is an attractive solution to India's rural electrification problem as it is available across the country for most days of the year, which essentially avoids costly transmission infrastructure to geographically dispersed rural localities.

Bryan et al [27] also come to the conclusion that nanogrids would be useful for rural electrification. They find that nanogrids could be useful to defer upgrades and provide voltage support to New Zealand’s weak rural electricity network. The continuance of supply clause in New Zealand’s Electricity Act states that as and from 31 March 2013, distribution companies were released from the obligation to supply existing customers. The implication of this act is that customers in rural locations will began to pay the true cost for their line-delivered electricity, which was subsidised. Forming a renewable-based system such as a nanogrid may be viable under these circumstances, especially if the system supplies a cluster of loads. It would probably be more economical to create a local cluster that serves multiple customers than build a power system for each individual customer. The cost of providing electricity to a house with a hybrid system is higher than supplying grid electricity but by aggregating loads the viability of such systems can be improved. This is due to load factor improvement and economies of scale. Another use for nanogrids in rural New Zealand is to service houses serviced by single wire earth return systems. These systems have high resistance lines and long feeders which are in need of upgrade. Installing nanogrid systems could defer the need to upgrade these lines by reducing load. Deferring upgrades could result in significant monetary savings.

Nordman et al [28] suggest that nanogrids are the solution to the problem of matching electricity demand to supply on a large scale. They can be used to implement the “smart grid” concept. On a smaller scale they give the example of a village in a developing country which needs access to reliable access to electricity to power fridges for storing medicine. In this example a nanogrid could be used to take advantage of both AC power from generators and DC power from local renewable sources to provide the villagers with electricity.

Alternative Nanogrid Concepts

The definition of a nanogrid has not been standardised. The nanogrids used in this thesis are of the type defined by Nordman [2]. However the term is also commonly used to refer to small microgrids. The use of these types of nanogrids could be important due to recent improvements in power electronics [29]. This is due in part to increased interest in renewable energy sources which produce DC electricity. Most domestic loads use DC power which must be transformed from AC power supplied by the grid. This further fuels interest in developing domestic nanogrids to efficiently allow the use of both AC and DC power simultaneously.

Considerable research has been undertaken into developing converters to facilitate distributed DC generation in a traditional grid that is designed for AC production. A converter that can simultaneously supply AC and DC loads from a single DC input is presented in [30] and [31]. Haroun et al [32] give reasons why a DC nanogrid is preferable to an AC nanogrid. They present a power converter to transform low-voltage and low-power generators, like PV panels or fuel cells, to a main DC 380-V voltage distribution bus. The concept of a household energy control centre (ECC) is introduced by Dong [33] as a way of interconnecting a DC nanogrid system with distributed generation capacity to the traditional AC grid. Dong proposes that that these ECCs are like routers for electricity connecting micro, mini and nanogrids together. In this proposed system the various grids can be decoupled in event of blackouts or outages, thus protecting the overall electricity distribution system from cascading system failure. A working prototype of an ECC is presented in [34]. Sankar et al [35] examine the use of local battery storage in a DC nanogrid to ensure continuity of power. Instead of using different dedicated converters from various uni-directional renewable sources, they propose a single stage boost converter with multiple inputs that can efficiently charge a battery.

Schonberger et al [36] examine the possibility of using a stand-alone DC nanogrid to power facilities in remote locations without access to AC grid power. Most nanogrid systems rely on a central controller to balance loads with supplies. To improve the reliability of the system the authors propose the use of DC bus signalling (DBS). DBS is a means of controlling a hybrid renewable system in a distributed fashion. This control strategy maintains the reliability inherent in the structure of the system by using the DC bus itself as the communication link. Bryan et al [37] use DBS to maintain power balance in a nanogrid with fluctuating sources and loads.

Trading Algorithms

Several suggested protocols have been put forward for the operation of nanogrids. Mitra et al [38] look at the basic operating conditions for nanogrids. They propose that at the bare minimum Kirchhoff's law for power flow conditions must be satisfied on the physical power level and that operating rules must be established on the data level. With these basic conditions in place they suggest improving the system by implementing electricity market and load management systems.

Doyle et al [39] achieve this, implementing a tâtonnement market mechanism which uses negotiations between nanogrids to converge on a price for electricity. To obtain optimal performance a nanogrid must use price negotiation and load scheduling. Due to conflicting goals amongst competing nanogrids and the electricity utility the process of negotiating prices will consist of multiple offers and counter offers. The tâtonnement algorithm is used to resolve this. Tâtonnement is an iterative process where agents receive price signals from an imaginary auctioneer that creates prices based on demand. It keeps sending out new price signals until a consensus is reached. Agents act in a greedy manner and attempts to obtain the best price possible using a brute force search to find the maximum of a utility function. The utility and the nanogrids take turns altering their prices until equilibrium is reached or a maximum allowed number of iterations have taken place. To insure convergence an adaptive step size is used when altering the price for each iteration.

Mohensian et al [17] outline a load management system that schedules loads in an optimal and automatic fashion to minimize electricity prices for a consumer while reducing the PAR of the residence. To do this, the energy scheduling of a house is formulated into an optimization problem that minimizes the electricity expenditure of the house with an RTP pricing structure in place. In the proposed system RTP information is broadcast by the utility to users over a digital communication infrastructure to each end user.

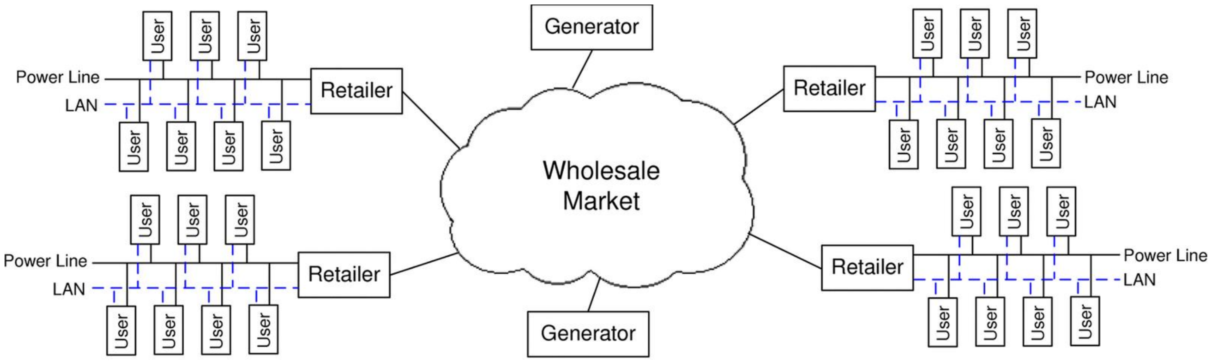


Figure 11: Electricity market where retailers provide users with RTP [17].

Each end user has a central controller installed which solves an optimisation problem that achieves a trade-off between minimising electricity payments and minimising waiting time for the operation of household appliances in response to the prices announced by the retailer. The resulting energy consumption schedule is then applied to all appliances with on/off commands broadcast wirelessly over a wireless home area network (WHAN).

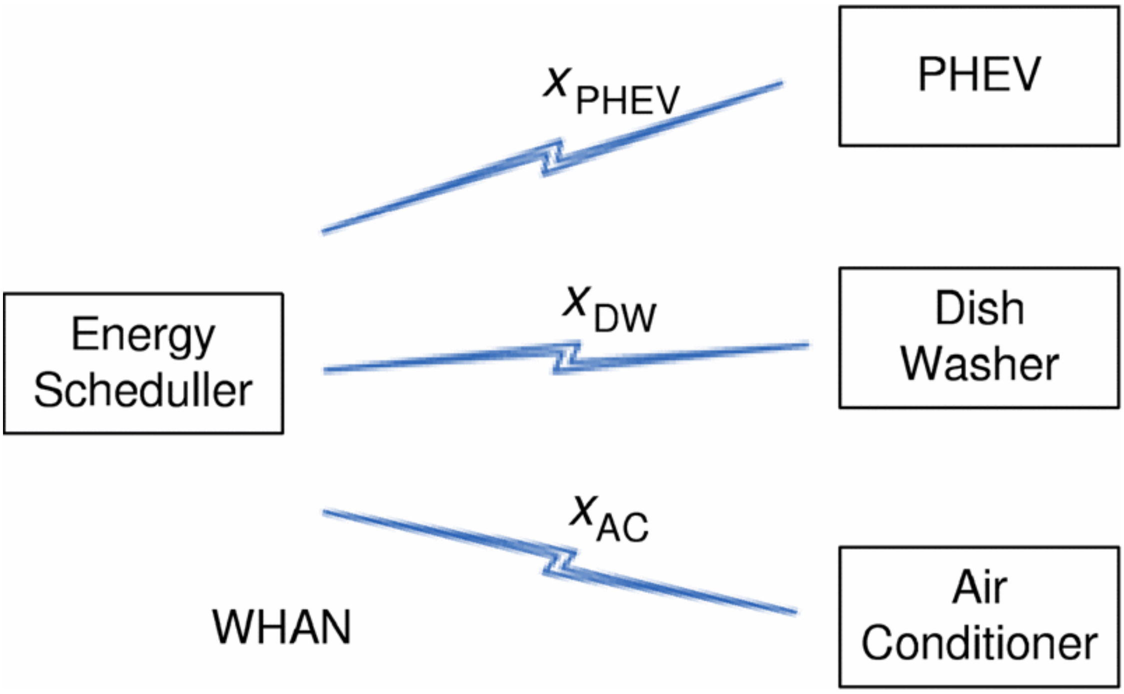


Figure 12: Energy consumption schedules being sent to appliances [17].

The proposed scheduling system works well assuming the prices for the next twenty four hours are known in advance. This assumption holds in a DAP model where the utility announces hourly prices a day in advance. However more dynamic pricing models should be considered where prices are only known a few hours ahead of time. The period of time ahead that prices are supplied is known as the price announcement horizon. In order to use load scheduling in a situation where the load scheduling horizon is less than twenty four hours a method for price prediction must be implemented. Prices vary on a daily basis but there are certain recurring trends which can be used to predict future pricing. Implementing a pricing model by looking at prices in previous years or months is not feasible due to major fluctuations in price[17]. An effective price prediction model can be assembled by looking at prices from yesterday, the day before yesterday and the same day last week.

Linear Programming

This thesis uses linear programming techniques and a distributed system of nanogrids to lower the electricity expenditure of a household.

“When a decision problem requires the minimisation of a linear form subject to linear inequality constraints, it is called a linear programme.”[40] The study of linear programming provides insight into the problem of minimising a convex function whose variables must satisfy a system of convex inequality constraints. A linear problem has a feasible region which is a convex polytope. This is a set defined as the intersection of finitely many half-spaces where each of the half spaces is defined by a linear inequality. Its objective function is a real-valued affine function defined on this polyhedron. A linear programming algorithm finds a point in the polyhedron where this function has the smallest (or largest) value if such a point exists.

The problem of load scheduling can be viewed as a combinatorial problem which can be solved using Linear programming techniques [17]. With a suitable pricing model in place, load scheduling of appliances can be optimised to lower electricity expenditure. If houses being serviced by an electricity supplier were to implement a load scheduling system of this nature the supplier could implement demand response by adjusting the price of electricity in response to forecasted demand. In this way a supplier could balance loads improving the PAR of the grid while consumers could stand to make significant savings on electricity bills.

This thesis designs and implements a prototype of a household appliance scheduling system that uses nanogrids to control appliance access to electricity. The use of distributed generation is also investigated as a method of reducing electricity expenditure. Since the nanogrid technology used to implement the load scheduling system can be also be used to manage local power sources, it is a logical choice to design a system that manages household electricity using load scheduling and distributed generation management in a complimentary manner.

Chapter 3: Design

The overall aim of this thesis is to design a residential electricity management system that lowers house hold electricity payments and PAR. The system developed uses appliance load scheduling with the optimal and automatic framework described by Mohsenian-Rad et al [17] and optimal local renewable power use to intelligently lower electricity expenditure. It is implemented on the lab equipment assembled by Doyle et al [39]. Since the design uses a combination of two methods of electricity management they are first presented separately. At the end of the chapter the two are combined to create an electricity management system that features local renewable power use in addition to appliance load scheduling.

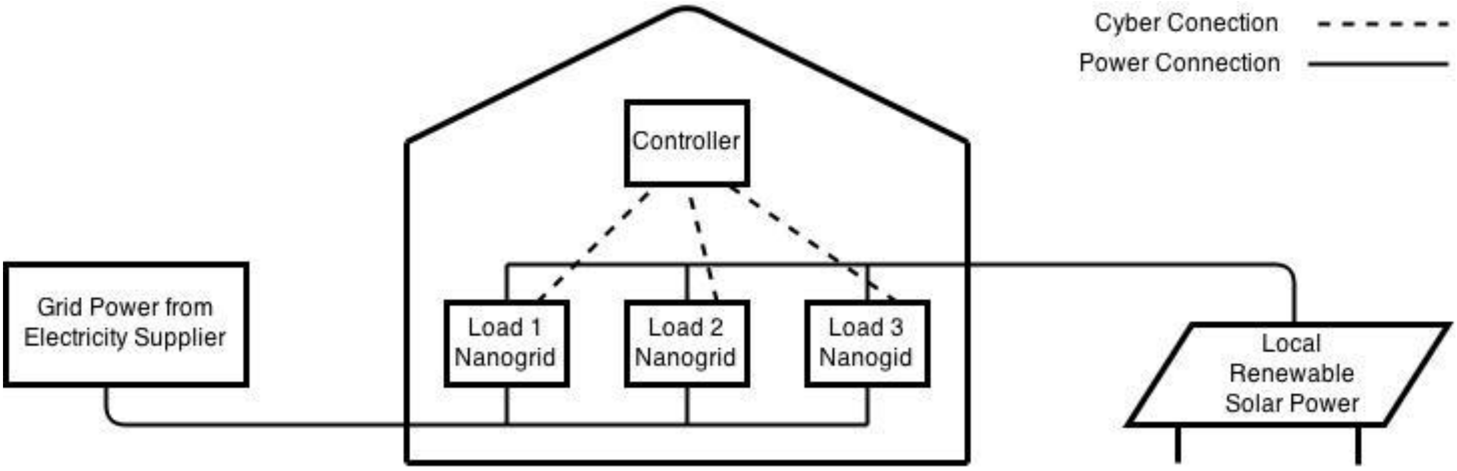


Figure 13: Household with multiple appliances and power sources

The system consists of four main components: a set of nanogrids, a central controller, a local renewable energy source and a connection to the electricity grid. Each nanogrid manages the power requirements of an appliance in the house. When a user wants to run an appliance they enter a start time and an end time for the job into the appliances corresponding nano-grid controller. The nanogrid controller sends this information to the house's central controller. The central controller splits each job into smaller sub-jobs and schedules these sub-jobs so the overall job will be done inside the time window specified by the user.

Using RTP pricing information received over the internet from the electricity provider it schedules the sub-jobs to run at times when electricity is cheapest. This scheduling method is described in the next section of this chapter. In addition to this load scheduling the central controller also monitors the amount of electricity currently stored in the battery of the house's local renewable energy system. After an appliance job has been scheduled the central controller goes back over the schedule and further reduces the electricity expenditure of the house by ordering the nanogrids to use this local renewable energy to complete the most expensive sub-jobs. This local renewable energy utilization method is described in its own section later in this chapter.

Load Scheduling

This central controller implements an energy consumption scheduling framework which achieves a trade-off between minimising a consumer's electricity expenditure and minimising the time an appliance delays operation as a result of abiding by this schedule. To do this it requires real time pricing tariff information from the consumer's electricity supplier. The system consists of a set of appliances denoted by A.

We begin by describing the characteristics of a single load. For each appliance $a \in A$ we define an energy scheduling vector x_a:

$$x_a \triangleq [x_a^1, \dots, x_a^H] \qquad (2)$$

H represents the scheduling horizon which is the furthermost hour that will be taken into consideration. For example an H value of twenty-four would indicate that at the most the system schedule appliance sub-jobs into any of the next twenty-four hours. For each $h \in H$, x_a^h represents the amount of energy consumption scheduled per hour for appliance a. The schedule interval $[\alpha_a, \beta_a]$ gives the time interval over which the appliance owner feels operation is acceptable. For example, choosing $\alpha_a = 1pm$ and $\beta_a = 6pm$ would indicate that the user wants the operation to start any time after 1pm but it must be finished by 6pm.

$E_a$represents the total energy required for the appliances operation. Given α_a, $\beta_a$and E_a it is required that: (3) is true.

$$\sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a \tag{3}$$

The distribution of $E_a$into the elements of x_a is the purpose of the load scheduling system. Further to (2) there is a second constraint on the system that must be observed. Some appliances have a minimum standing power requirement or a maximum allowable power level. These are given by γ_a^{min} and γ_a^{min}. When this is taken into account along with (2) we have the constraints that describe all valid choices for the energy scheduling vectors. We define a feasible scheduling set $\mathcal{X}$ as:

$$\mathcal{X} = \left\{ \begin{array}{c} \mathbf{x} \,\middle|\, \sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a, \forall a \in A, \\ \gamma_a^{min} \leq x_a^h \leq \gamma_a^{max}, \forall a \in A, h \in [\alpha_a, \beta_a], \\ x_a^h = 0, \forall a \in A, h \in H/[\alpha_a, \beta_a] \end{array} \right\} \; where\, \mathbf{x} \triangleq (\mathbf{x}_a, \forall a \in A) \tag{4}$$

l^h denotes the total hourly energy use of the appliances $a \in A$ at each hour $h \in H$:

$$l^h \triangleq \sum\nolimits_{a \in A} x_a^h \tag{5}$$

The price of electricity for each hour $h \in H$ is denoted by p^h. The list of prices for the next H hours is broadcast by the electricity provider each hour. The users total electricity payment for all appliances in the scheduling horizon is given by:

$$\sum_{h=1}^{H} p^h l^h \tag{6}$$

This system also aims to minimise the amount of time a user must wait for a job to be completed. This can be modelled as:

$$\sum_{h=1}^{H} \sum_{a \in A} \rho_a^h \ x_a^h \tag{7}$$

The waiting parameter ρ_a^h is modelled for each $a \in A$ as:

$$\rho_a^h = \frac{(\delta_a)^{\beta_a - h}}{E_a}, \quad \forall a \in A, h \in [\alpha_a, \beta_a] \tag{8}$$

By increasing the value of $\delta_a$the cost of waiting is increased so by altering δ_aa user can specify the urgency of a job. Roughly speaking this offers the user three modes of operation in the finished system. When $\delta_a = 1$ maximum electricity cost reduction is achieved as there is no penalty imposed for scheduling a sub-job for a later time. When $\delta_a > 1$ potential cost reductions are reduced as earlier time slots are preferred to later time slots. If the price of electricity at earlier slots is high enough the sub-jobs will still be scheduled for later slots. When $\delta_a \gg 1$ the electricity price of a slot becomes irrelevant as all the algorithm is interested in is scheduling the job as early as possible.

By combining (6) and (7) a minimization problem(9) can be formulated which when solved with the energy consumption scheduling vectors x_a used as optimisation variables will provide an optimum load schedule for all appliances $a \in A$. The schedule will provide a trade-off between energy cost and waiting cost that is weighted by γ_{wait}. Mohensian et al [17] suggest using $\gamma_{wait} = 1$ as a typical value in the system so that is what will be used in this implementation.

$$\textbf{minimize} \sum_{h=1}^{H} p^h \sum_{a \in A} x_a^h + \gamma_{wait} \sum_{h=1}^{H} \sum_{a \in A} \frac{(\delta_a)^{\beta_a - h} x_a^h}{E_a} \tag{9}$$

Local Renewable Utilization

To further reduce electricity expenditure a second method of energy management for the central controller was devised. The load of each nanogrid is a household appliance $a \in A$. To turn on the appliance the user inputs the time period $[\alpha_a, \beta_a]$ over which they wish the appliance to operate. This information is sent wirelessly from each nanogrid to the central controller. The controller takes this information and checks if there will be enough renewable energy in the battery to meet the demand. It attempts to forecast the amount of renewable energy that will be available by accessing real-time weather forecasts online and using this to estimate how much power will be produced by the solar panels each hour. It measures the level of the battery and adds the estimated amounts to forecast how much will be available hourly. The controller receives RTP electricity prices from the electricity provider via the internet and assigns the nanogrids access to the renewable energy at the times it would be most expensive to take power from the grid.

To assign hourly access to renewable or grid power the central controller:

1. Looks at the appliance load sub-jobs scheduled by the load scheduler.
2. Ranks them by the cost of electricity from the grid at that time
3. Starting with most expensive, access to renewable energy is assigned based on:
    - If there is adequate renewable energy to satisfy the load at that time
    - It won’t consume energy needed to supply an appliance at a later, more expensive slot

Complete System

By implementing both the load scheduling method and the local renewable energy utilization method the central controller can reduce the electricity expenditure of the house hold by a greater amount than if it just used either individually. This will be referred to as the complete system. In the complete system the user enters a period of time over which they want their appliance to get a job done through the appliance nanogrids. Each nanogrid sends this information to the central controller where the times the appliance will run are determined using load scheduling. This schedule is then used as the input into the local renewable utilization method which determines when to use the local renewable power. When this is complete the central controller then sends instructions back to the nanogrids instructing them which power source to use for their appliance as well as what time to do so.

Figure 14: Complete system controller behaviour

Chapter 4: Implementation

Hardware

The nanogrid prototype and lab setup used to implement the system in this thesis were designed and assembled by Donal O'Mahony [39], a professor of computer science at Trinity College Dublin.

Nanogrid Prototype

The nanogrid prototype consists of a set of relays controlled by a Raspberry Pi computer. The "B" model Pi is a credit card sized computer with a 700MHz ARM CPU running the ARMv6 instruction set. It has 512MB of RAM, 3 USB ports and sound (3.5mm jack) and video output (HDMI). A powered USB v2.0 hub is used to connect a mouse, a keyboard and a "Wi-Pi" USB Wi-Fi adapter. A micro SD card preloaded with the Raspberian operating system provides the devices persistent storage. The Raspberry Pi acts as the controller of the nano-grid. It handles networking with other nanogrids, processing data and managing access to power for the loads it is responsible for.

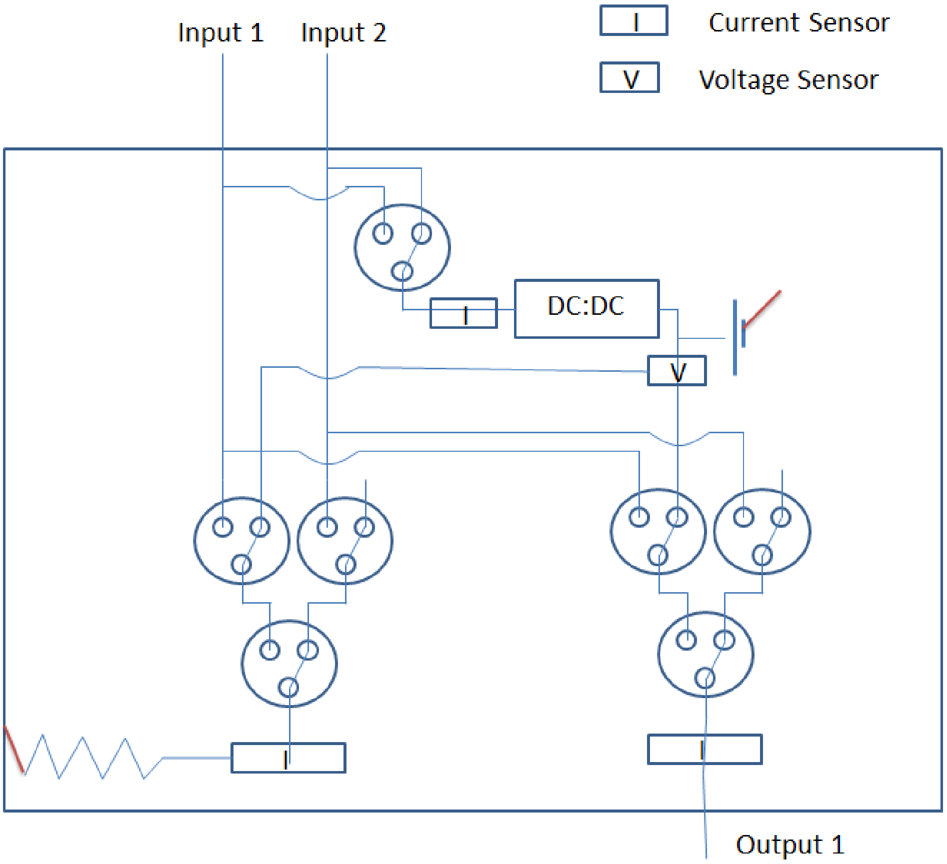


Figure 15: Nanogrid relay diagram [39]

In order to manage a loads access to power the Pi is connected via its GPIO pins to an array of Schrack v23092-a1060-a301 relays. They are set-up as shown in Figure 15. By manipulating these relays a path can be created for power to flow from inputs one or two to the output or the load. An Allegro ACS712 Current Sensor allows the Pi to keep track of current flows through the nanogrid. Keeping a log of this current flow allows the nanogrid handle administration of its operation and adds security to the nanogrid network. By having a consumer nanogrid keep track of energy received and a supplier nanogrid keep track of energy dispatched; it can be clearly identified if any third party is stealing electricity from the line.

A 20W bulb is used to represent a load on the prototype. A battery and charging apparatus are also connected to the prototype but these were not used in this thesis.

In order to demonstrate that the system implemented in this project would work with multiple nanogrids a second Raspberry Pi rig was set up. This Pi was set-up in a similar manner to first but the relay array in figure 15 was replaced with a breadboard with two LED's. These LED's turn on and off to reflect the decisions made by the central controller while demonstrating. The central control system was run on a laptop in the lab but could just as easily be run on a Raspberry Pi or nanogrid prototype of its own.

Lab Set-up

The lab where work for this thesis was carried out was specifically designed for nano-grid research. Solar panels are installed on the roof and their power is routed to a 12V deep cycle battery with a storage capacity of 260Ah @ 20h. The charging and discharging of this battery is handled by a Flexmax charge controller which protects the battery from overcharging. This power is made available from a 12V DC bus through wall sockets throughout the lab. A second, separate 12V DC bus also runs around the lab. This bus is powered from the mains via a Dell N750P-00 power supply. There are many valid choices of voltage level for DC nanogrid research but 12V was chosen for safety. Each DC bus is used as an input into the nanogrid prototype.

A Davis Venture Pro2 weather station is installed to provide accurate weather data. Of particular interest is the solar measurement functionality which measures solar power available in W/m^2. It was planned to use this information along with scraped weather data to implement a function to predict the amount of renewable energy that would be produced by the solar panels on any given day. However this turned out to be beyond the scope this thesis.

The final piece of lab equipment used is a specially provisioned internet router to facilitate wireless communication between the Raspberry Pi's as under normal circumstances the security measures in place on the college network would make this impossible.

Software

All code developed for this thesis is written in Python 3.0. This language was chosen for three reasons:

1. Python is the native language on the Raspberry Pi.
2. Python allows for quick code turn-over making it suitable for prototype design.
3. Python has a diverse selection of quality libraries.

XMLRPC

XML-RPC is a remote procedure call method that uses HTTP to transport XML. Clients can use it to call methods with parameters on a remote server and receive structured data back. This module handles marshalling of data and objects for sending over the wire. XMLRPC is used to send communications between the nanogrids and the central controller.

TkInter

TkInter is the standard GUI package used for python. It's a thin object-orientated layer on top of Tcl/Tk. Tk is an open source, cross platform toolkit that provides GUI widgets for building GUIs. The user interfaces to monitor and control the behaviour of the nanogrids is created using TkInter.

PuLP

PuLP is an open source linear programing modeller. It's a package that allows mathematical problems be described and solved using the python programming language. PuLP provides an interface to numerous mixed-integer linear programming solvers.

Quick2wire

Quick2wire allows the use of I^2C with the Raspberry Pi. I^2C is a multi-master, multi-slave, single ended serial computer bus which is used to connect motherboards to lower-speed peripherals. This allows devices with different clock speeds to communicate.

Rpi

Rpi is a python GPIO interface for the raspberry pi. GPIO pins act as a physical interface between the raspberry pi and the rest of the world. In the nanogrid prototype they are used to open and close relays.

System Behaviour

Two classes are created to implement the systems outlined in chapter 3: a LoadNanoGrid class to operate the individual appliance nanogrids and a SourceNanoGrid class to operate the central controller.

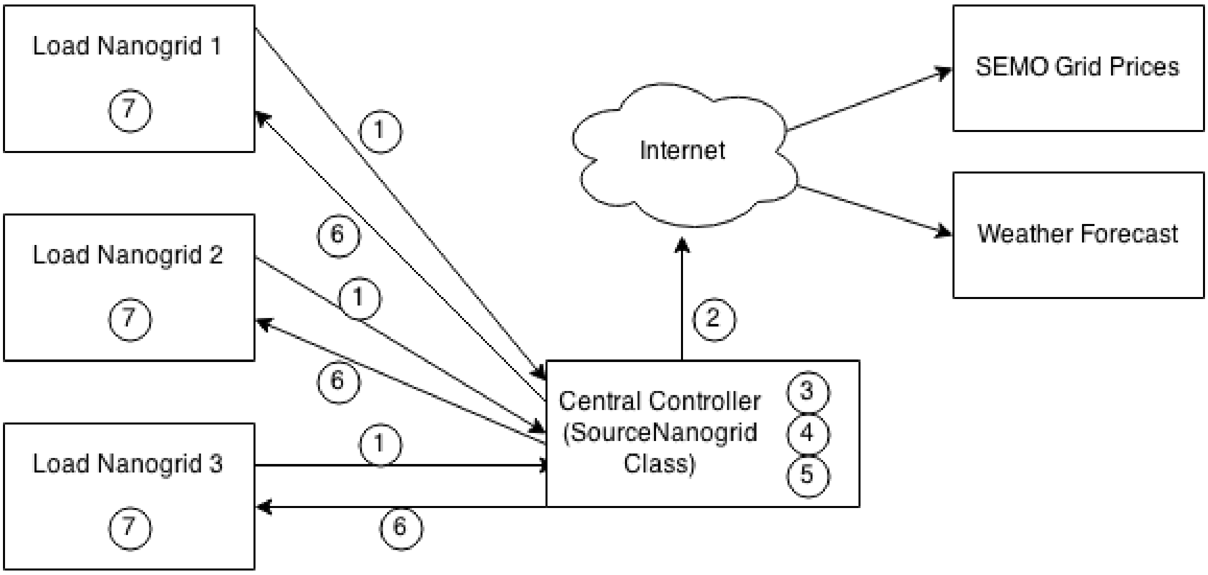


Figure 16: System Dialogue Diagram

1. Load nanogrids send scheduling requests to the central controller when a user schedules a job for the nanogrids corresponding appliance. To request scheduling the load grid sends the controller the time period over which the user wishes the job completed and information about the appliance load.
2. The central controller checks the internet for RTP electricity price information and weather data for the next twenty-four hours (This part of the code was not completed due to time constraints).
3. The controller uses the weather data to predict how much renewable energy will be produced by the houses' solar panels over the next twenty four hours.

4. The controller schedules the loads it received in step 1 using the pricing information from the internet and the load scheduling algorithm described in chapter 3.
5. The controller uses the local renewable energy utilization algorithm described in chapter 3 to decide the best times to use the locally generated power.
6. The controller sends each load grid an order for its appliance for that hour. This can be one of three orders: turn off the appliance, power the appliance from the grid or power the appliance from the renewable energy.
7. The load grids carry out the orders they received.
8. Each hour the system returns to step 2 and repeats the cycle. The user can schedule new jobs at any time on the load grids and the controller will take these new jobs into account when it does its calculations on the next turn of the hour.

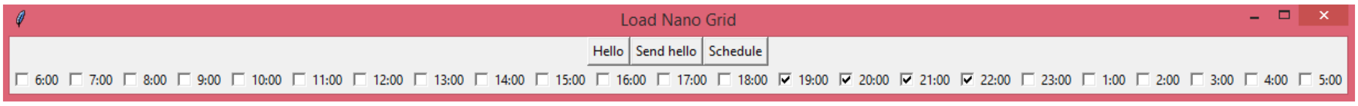
LoadNanoGrid Class

The load nanogrid class runs on the nanogrid prototype. Its function in the system is to control for a major household appliance, like a washing machine or PHEV. It takes scheduling data from the user and sends it to the central controller in the house for processing. The load nanogrid then receives and carries out instructions from the central controller dictating when its appliance can access energy using the Rpi GPIO module.

The LoadNanoGrid contains the following variables to store information on itself and the other nodes in the system:

- nanoGridID: Each nanogrid is assigned a unique name.
- IPAddress: Each nanogrid is assigned an IPAddress on the network using the Raspberian Wi-Fi Config utility.
- loadSize: Each nanogrid knows the energy requirement of the appliance it is responsible for.
- schedule[]: An array for storing the users choice of running time for the appliance.

Upon starting the programme an instance of a class called Display is run. Display creates and displays the user interface shown in figure 17 using the TkInter GUI package and creates an instance of LoadNanoGrid.



☐ 6:00 ☐ 7:00 ☐ 8:00 ☐ 9:00 ☐ 10:00 ☐ 11:00 ☐ 12:00 ☐ 13:00 ☐ 14:00 ☐ 15:00 ☐ 16:00 ☐ 17:00 ☐ 18:00 ☑ 19:00 ☑ 20:00 ☑ 21:00 ☑ 22:00 ☐ 23:00 ☐ 1:00 ☐ 2:00 ☐ 3:00 ☐ 4:00 ☐ 5:00

Figure 17: TkInter load grid graphical user interface

The main loop of the programme is this display which waits for user input. In a separate thread a listener function is started. The listener function starts an XMLRPC server with functions that control the relays of the nanogrid. These functions are invoked remotely by the central controller.

When the user has specified the time period over which they would like the appliance to run they click the “Schedule” button which sends the contents of this array and load size to the central controller. If the schedule is received successfully a confirmation notice will be received.

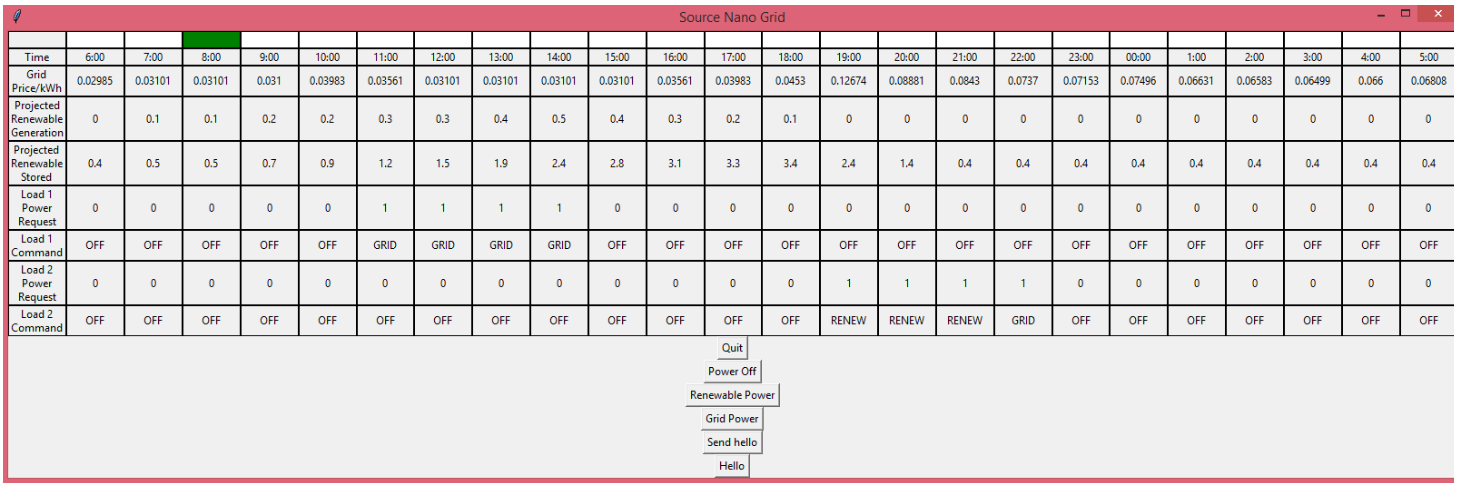
The “Hello” and “Send hello” buttons allow the user to ensure a connection has been correctly established between the load grid and the controller by sending and printing message strings on their respective consoles.

SourceNanoGrid Class

The source nanogrid class runs on a laptop in the lab set-up. Its function in the system is to represent a central controller in a residential house which takes scheduling requests from appliances and controls their access to power to minimise the electricity bill of the household. It does this by scheduling the appliances to run at times when grid electricity is cheap. After scheduling it drives the cost down further by using available local renewable energy for the most expensive time slots.

The SourceNanoGrid contains information on every other node in the system. It stores this in a “Load” object containing nanoGridID, IPAddress, loadsize, and schedule[] for any load grids connected to the controller. One “Load” object is created for every load added to the network.

Upon starting the programme an instance of Display is run. Display creates and displays the user interface shown in figure 18 and creates an instance of SourceNanoGrid.



			🟩																					
Time	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	1:00	2:00	3:00	4:00	5:00
Grid Price/kWh	0.02985	0.03101	0.03101	0.031	0.03983	0.03561	0.03101	0.03101	0.03101	0.03101	0.03561	0.03983	0.0453	0.12674	0.08881	0.0843	0.0737	0.07153	0.07496	0.06631	0.06583	0.06499	0.066	0.06808
Projected Renewable Generation	0	0.1	0.1	0.2	0.2	0.3	0.3	0.4	0.5	0.4	0.3	0.2	0.1	0	0	0	0	0	0	0	0	0	0	0
Projected Renewable Stored	0.4	0.5	0.5	0.7	0.9	1.2	1.5	1.9	2.4	2.8	3.1	3.3	3.4	2.4	1.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Load 1 Power Request	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Load 1 Command	OFF	OFF	OFF	OFF	OFF	GRID	GRID	GRID	GRID	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF
Load 2 Power Request	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0
Load 2 Command	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	OFF	RENEW	RENEW	RENEW	GRID	OFF	OFF	OFF	OFF	OFF	OFF	OFF

Figure 18: TkInter source grid graphical user interface with two load grids connected

A second thread is started to facilitate an XMLRPC server. This server’s purpose is to listen for incoming scheduling requests from load grids and store these schedules in the appropriate Load object.

The main loop of the programme is the display which shows the user a visual representation of the scheduling and local renewable energy algorithms at work. The controller starts the decision making process by getting the grid prices for the next twenty four hours from the utility. It was originally planned to code a web scraping function to update this hourly, but this functionality was not implemented due to time constraints on the thesis. In place of this functionality, a sample twenty four hours of electricity prices from the SEM-O website [11] are stored in an array. Next it predicts how much renewable energy will be produced in the coming hours.

Load scheduling is now carried out by solving equation 9 from chapter 3 using the PuLP linear programming modeller. The variables for the problem are dynamically created by looking at how many hours are in the requests from each appliance. As each variable is created it is specified that it must satisfy the constraints set out in equation 4. Once the linear programming problem is solved and an optimum load schedule has been obtained, the local renewable utilization algorithm is applied to the result. With the calculations finished, the controller sends out one of three instructions to each load; RENEW if the appliance is scheduled to be on for the coming hour powered by renewable energy, GRID if the appliance is scheduled to be on for the next hour but with grid power instead of local renewable and OFF if the appliance should not be turned on this hour. The green rectangle at the top of the display indicates the current time. At the turn of each hour all of the algorithms are run again and a new set of instructions are sent out to each load grid.

The “Quit button” will switch off the whole system including the load grids and turns off the appliances. The other buttons can be used to manually switch on and off appliances. Their purpose is to ensure a connection has been correctly established between the controller and the load grids.

Chapter 5: Simulation Results

Simulations were run to measure effects of the proposed system on the electricity expenditure and PAR of a household. The simulations use grid prices from the SEMO database [11] covering the period between the first and the thirtieth of November 2014. These hourly wholesale electricity prices are used to simulate a RTP pricing system where the household pays different prices based on the time of day they access electricity.

Randomised Appliances

People in a real household do not use the exact same appliances at the exact same times every day. As a result the daily load profile of a house changes. To reflect this, a simulation is run where a different set of loads is chosen each day. Ten appliance schedules, which dictate the earliest possible starting time and the latest acceptable finishing time for a job, are selected randomly from a set of thirty possibilities that were made up for this simulation. These schedules vary between three and seven hours long and are spread uniformly across a twenty four hour period. They are given in appendix C. Each appliance has a randomly chosen power requirement of E_a = 1-6kWh. Each appliance also has a randomly chosen allowable hourly maximum of γ_a^{max} = 2-6kWh as certain appliances must spread their load over multiple hours. For example, certain plug-in hybrid electric vehicles (PHEV) charge at a rate of 3.3kW per hour even though a 30-40km drive requires 7-10kWh [41]. **For** all appliances γ_a^{min} = 0kWh. The waiting cost modifier was set to $\delta_a = 1$ so that the scheduler scheduled according to cost of electricity with no regard for getting the job done quickly.

Four cases are examined. In the first case no local renewable energy is available and no load scheduling is carried out. The appliance jobs are completed as quickly as possible using grid electricity. This represents a house with existing appliance management where appliances run as soon as the user turns them on. In the second case local renewable energy is made available and its use is optimised to lower electricity expenditure as described in the design chapter of this thesis. This is done to quantify the benefit of the local renewable utilization method compared to traditional appliance management. In the third case the availability of renewable power is removed but load scheduling is implemented. This is done to demonstrate the efficacy of the load scheduling method compared to traditional appliance management. This also allows a comparison to be made between the efficacy of the load scheduler method and the local renewable energy utilization method. In the final case the household has both local renewable power and load scheduling capabilities. This is to show that the two methods are complimentary and that a controller running both methods will outperform a controller running just one.

The results of this simulation are shown in figures 19 and 20, with the overall monthly figures given in table 1.

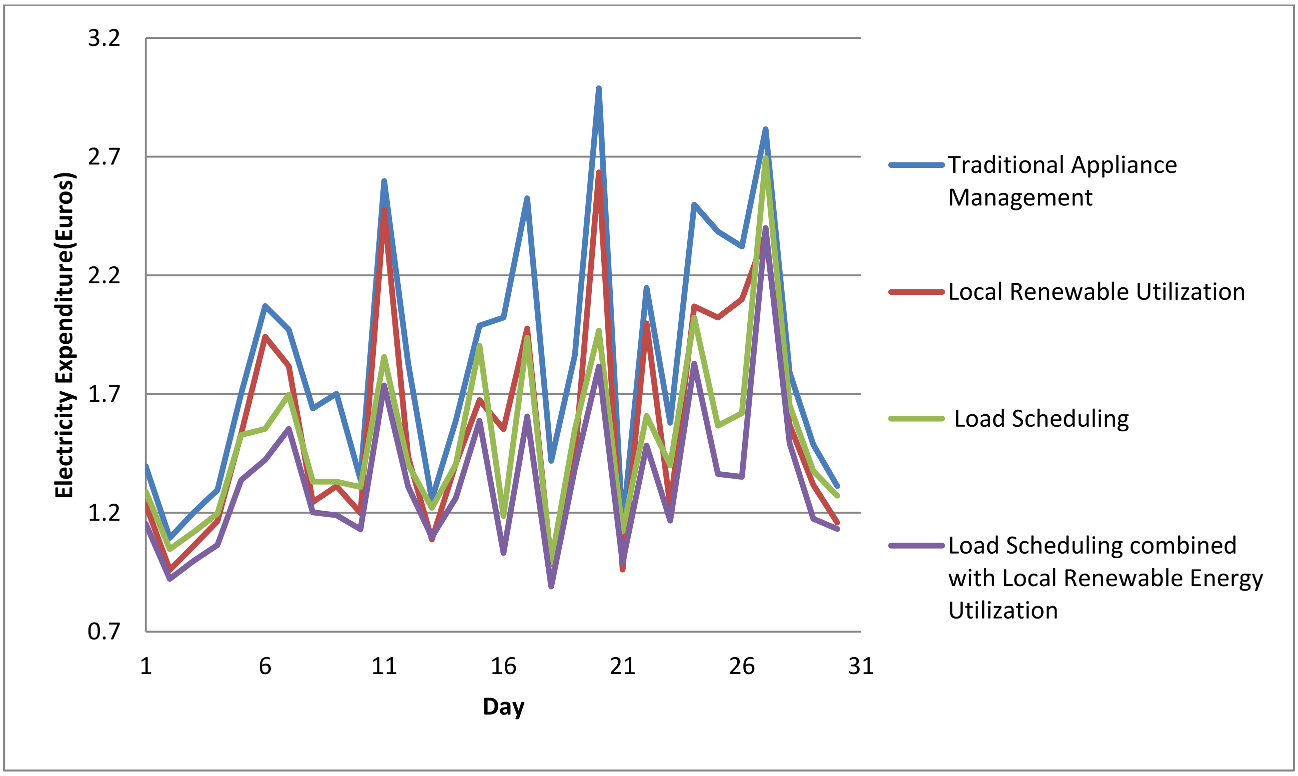


Figure 19: Electricity expenditure each day for a month with ten randomised appliances per day

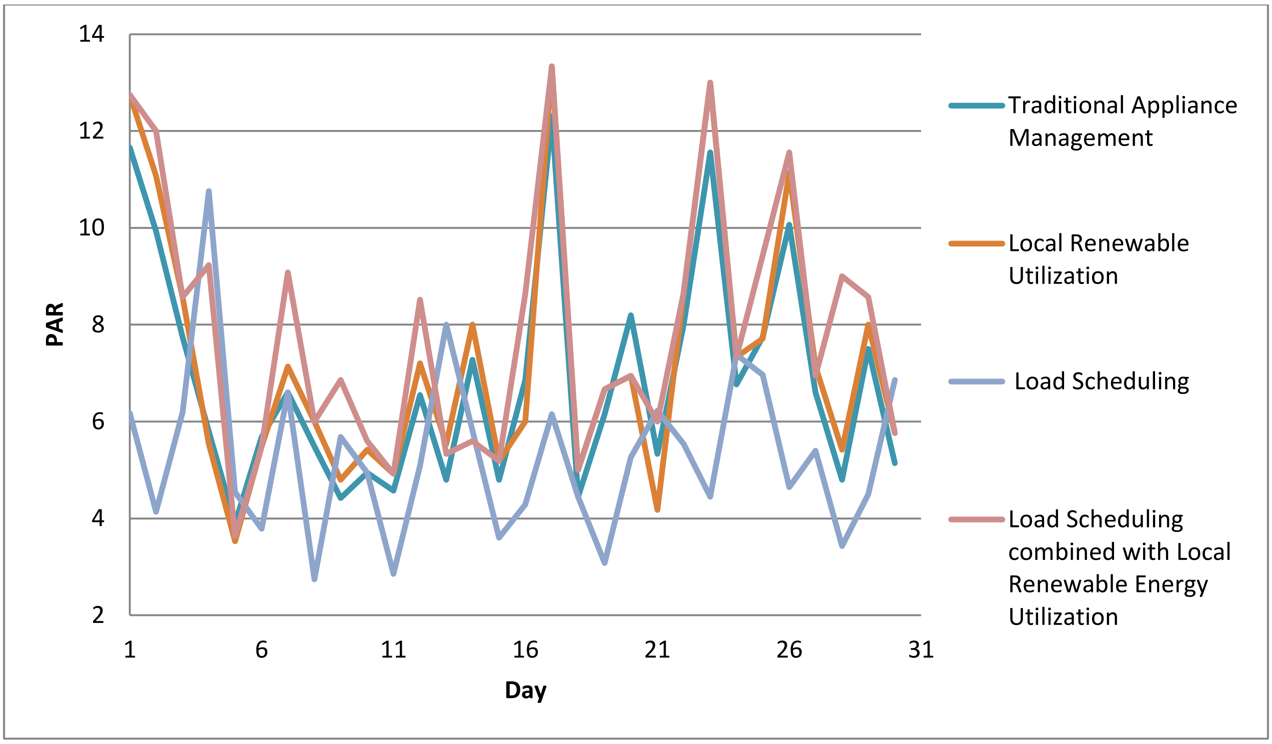


Figure 20: Peak-to-average each day for a month with ten randomised appliances per day

System	Monthly Expenditure (euro)	Change in Expenditure	Average PAR	Change in PAR
No System	54.97	-	6.85	-
Just Local System	46.91	-14.7%	7.24	+5.6%
Just Load Scheduler	45.16	-17.8%	5.31	-22.5%
Both Systems	40.08	-27.1%	7.85	+14.6%

Table 1: Random appliances monthly figures based on wholesale prices from SEMO

The effects on the electricity expenditure of a household using the energy management system can be seen in figure 19. The blue line representing daily electricity cost without any additional management shows the highest price every day. Conversely, the purple line representing electricity cost with the full system implemented is the lowest each day. The two components in the system are run individually to examine their individual effects. Looking at the green and red lines, both methods individually are able to reduce electricity cost every day. However, there is no day that either of them alone is more effective than the two combined. The values in table 1 demonstrate that the load scheduler saves more money (17.8%) than the local renewable energy system (14.7%). As the renewable energy method has a limited amount of renewable power to distribute each day it's less advantageous than scheduling on days where the overall load is high. Day eleven and day twenty demonstrate this. On these days of high load the red line clearly tracks the peaks in the blue line. On days of low load, like day two and day thirteen, the local renewable system outperforms load scheduling as with fewer loads available to shift load scheduling loses its efficacy. Combining the two methods results in a monthly saving of 27.1%.

The effect of these energy management methods on PAR is not as clear as their effect on expenditure. By looking at the graph in figure 20 and the values in table 1 we see that load scheduling generally reduces PAR but the local renewable energy management method increases it. On certain days load scheduling significantly reduces PAR. Days three, seventeen, twenty three and twenty six in particular show a marked improvement. Performance on days like these contributes to the overall monthly reduction in PAR of 22.5%. PAR shows an increase of 5.6% when the local renewable management system is used. PAR can be increased in two ways: by increasing the size of the largest peak load or by lowering the mean load. The local renewable system reduces the expenditure of a household by supplying appliances with renewable power when grid power is expensive. From the grids perspective at these points in time, which previously could be peaks in demand, the load is now zero. This lowers the mean load for the household, thus increasing PAR. The two systems combined increase PAR by 14.6%. This is probably due to load scheduling moving loads away from the most expensive slots. This creates slots that have zero loads. More zero load slots are then created by the renewable system further decreasing mean load and increasing PAR.

Typical Usage Case

The second simulation used a pre-set non-random selection of major appliances chosen to represent the energy usage of a typical house. These are given in table 2**.** Some of the appliances, like lightbulbs, are not suitable for load scheduling as they require a constant supply of power over duration of time they are in use. Load sizes are sourced from the Office of Energy Efficiency and Natural Resources Canada [42].

Appliance (a)	Power Required E_a (kWh)	Starting Time α_a	Finishing Time β_a	Max Hourly Power Use γ_a^{max} (kW)	Scheduling
PHEV	10	20:00	5:00	3.3	Variable
Washing Machine	1.2	17:00	20:00	1	Variable
Clothes Dryer	2.5	21:00	00:00	1	Variable
Dish Washer	0.9	18:00	5:00	0.5	Variable
Refrigerator	1.2	6:00	5:00	0.05	Fixed
10 Lightbulbs	1	19:00	00:00	0.2	Fixed
Heating	8	7:00	23:00	0.5	Fixed

Table 2: Non-random appliance schedules

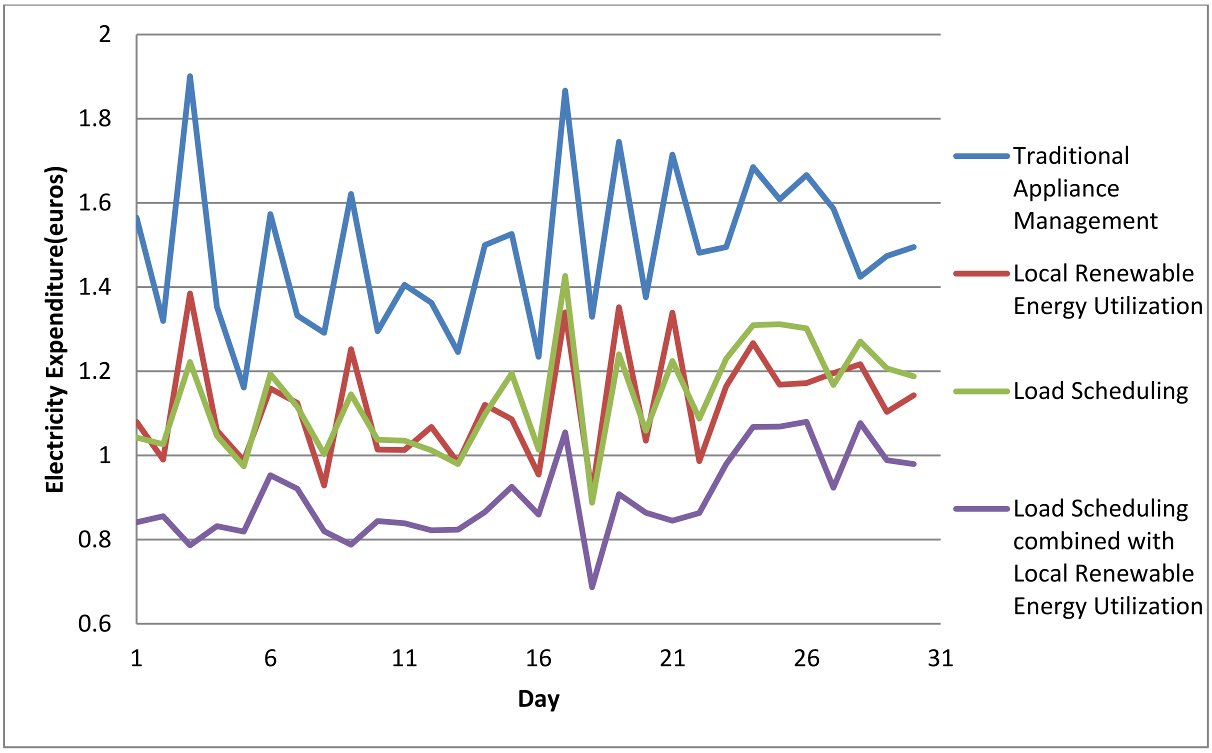


Figure 21: Electricity expenditure each day for a month with typical use case

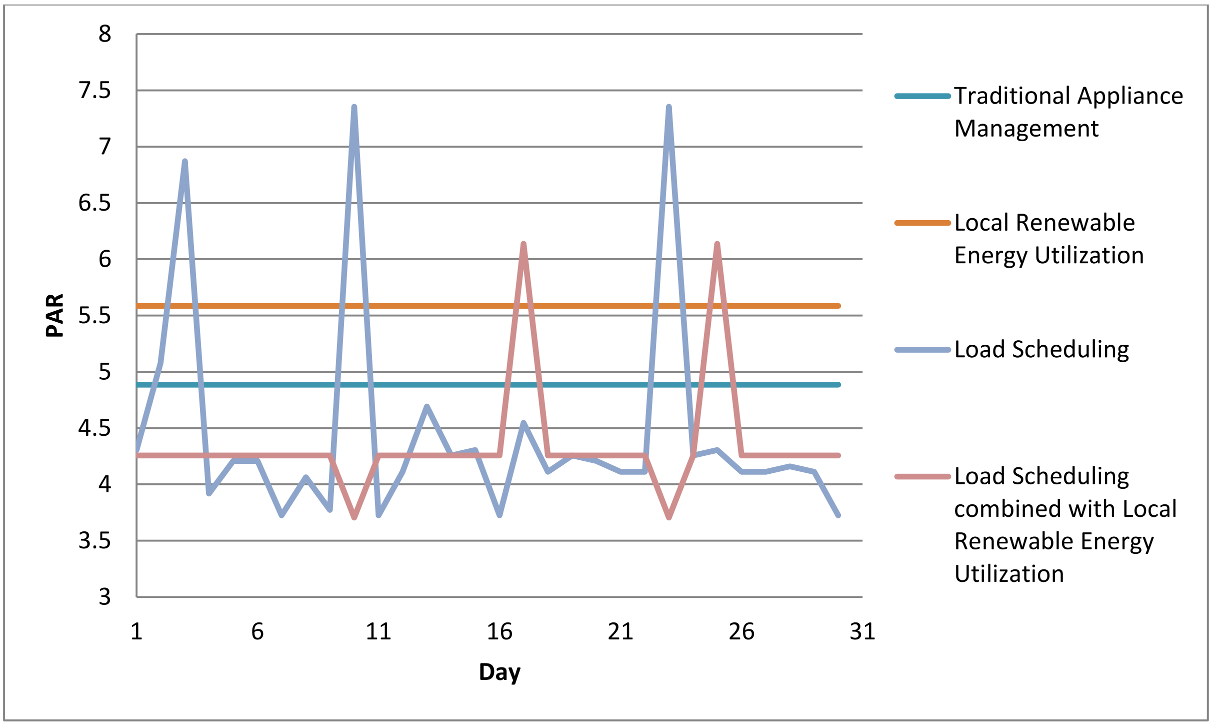


Figure 22: Peak-to-average ratio each day for a month with typical use case

System	Monthly Expenditure (euro)	Change in Expenditure	Average PAR	Change in PAR
No System	44.63	-	4.89	-
Just Local System	33.60	-24.7%	5.59	+14.3%
Just Load Scheduler	34.05	-23.7%	4.46	-8.7%
Both Systems	26.98	-39.5%	4.35	-11%

Table 3: Set appliances monthly figures

The effects on electricity expenditure in this case are consistent with what was observed in the previous case. From figure 21 and table 3 it’s clear using neither method is most expensive, using both methods is the most effective at reducing expenditure (39.5%) and the individual methods are in between in terms of reducing expenditure (24.7% and 23.7%). Once again, it depends on the day which individual system provides the most reduction in cost. The only thing that is changing day to day in this simulation is the daily prices being offered by the energy utility so from this graph the conclusion can be drawn that these prices have a bearing on which of the two methods is more effective.

Figure 22 and table 3 show the impact of the systems on PAR. PAR is lower on average than in the previous case (4.89 compared to 6.85, 5.59 compared to 7.24, 4.46 compared to 5.31 and 4.35 compared to 7.85). This can be attributed to the fixed schedule appliances. Since they cannot be load-scheduled away from expensive slots they stay evenly distributed so they do not contribute to the formation of load peaks. Since the appliances are the same every day PAR stays constant when load scheduling is not implemented. Just like in the last case using the local renewable method results in a higher PAR than using no system (14.3% increase). The load scheduling method results in an overall decrease in PAR (8.7%) but shows large spikes on day three, day ten and day twenty three. All of these days have abnormally high prices in the 5:00 -8:00 time slots. Since the variable schedule washing machine, clothes dryer and dish washer are scheduled for these times they are all scheduled into the same hour to avoid paying these high prices. This results in the observed peaks in PAR. Using both systems in this case results in an overall reduction in PAR of 11% but again there are two days that exhibit peaks; day seventeen and day twenty five. Interestingly two of the days that caused spikes in the just load scheduling days actually show a decrease in PAR when the local renewable system is introduced. Therefore one potential way to improve the systems PAR could be to intelligently disable and enable the local renewable system on a day by day basis.

Summary of Simulation Results

The results of the simulations in this chapter show that the household appliance management system presented in this thesis successfully lowers daily electricity expenditure. Furthermore we can conclude the two methods it uses to accomplish this are complimentary. On days of low load renewable energy utilization is effective while on days of high loads load scheduling is effective. While the system does alter PAR it does so in a variable way as on some days PAR is increased and on others it is decreased. When the systems two methods are split up, on average load scheduling has a positive effect but local energy utilization has a negative effect on household PAR.

Chapter 7: Conclusion

Traditional electricity grids have a top down centralised topology with large generating stations radiating power into progressively lower voltage lines to homes and businesses. These systems match electricity supply to demand by increasing power production in predominantly fossil fuel burning power plants. As the twenty first century progresses utilities are looking to novel methods of energy production to meet increasing demand for electricity. As a result the classic energy grid topologies are being put under pressure. The emergence of concepts such as distributed generation and demand response present an opportunity to address this problem, however in order to take advantage of these concepts appropriate energy management systems need to be developed.

As time progresses technology for processing and communicating digital information is becoming cheaper and more readily available leading to the gradual modernisation of the grid. A grid that uses these technologies to gather and act on the behaviours of consumers and suppliers is known as a smart grid. To make efficient use of this information the nanogrid concept has been proposed. A nanogrid is a single domain for voltage, quality, reliability, price and administration. It consists of a controller, a load and a set of gateways. Through the use of nanogrids it is possible to move away from the traditional top-down grid infrastructure design and move towards a bottom-up approach to electricity distribution which by its nature accommodates the use of distributed generation and load response.

The smart grid makes it possible for utilities to offer customers alternative pricing models which can be used as pricing signals to encourage load balancing on the grid. It makes sense for retailers to integrate pricing models like RTP, TOU and CPP into their tariff models to manage loads, reduce cost and maximise profitability. Doing so can save money for the consumer and increase the competitiveness of retailers, thus helping them manage and increase their customer base. However, the roll-out of these new technologies by retailers has been slowed by the perceived complexities and risks associated with their adoption.

In this thesis a literature review is carried out to examine the current state of the art of nanogrids and a system is designed and implemented on a nanogrid hardware prototype that reduces consumer electricity expenditure. This is achieved by using a combination of distributed renewable energy generation and linearly optimized load scheduling with a real time electricity pricing model.

The system consists of several raspberry pi computers connected wirelessly to exchange data and functionality using the RPC protocol. The central node in this network acts as a central controller sending instructions to the other nodes in response to appliance scheduling requests it receives. The other nodes are nanogrids which give electricity access to major household appliances based on the instructions received. To determine the instructions to send to the nanogrids the controller uses the scheduling requests as the inputs into two methods; a load scheduling method and a local renewable energy management method. Load scheduling is determined using RTP prices from an electricity provider. Appliance jobs are divided into sub-jobs which are scheduled using linear optimization to be done at times when grid energy is cheapest. The second method grants these scheduled appliance sub-jobs access to “free” local renewable energy at times when grid energy is most expensive. Access is only given at optimum times to insure that maximum potential electricity savings are gained from the use of local renewable power.

Two simulations are run to prove the effectiveness of the system in reducing electricity expenditure. The first simulates a month of electricity usage for a household with different randomly chosen appliance loads each day. It calculates daily expenditure and PAR for the house with the system installed and without the system installed. When the two cases are compared the use of distributed energy generation and load scheduling are found to be complimentary as they effectively reduce expenditure when used together. In this simulation the use of the system results in household electricity expenditure savings of 27.1%. The second simulation replaces the random appliance loads selection with a selection of appliance loads chosen to represent a real household. In this simulation household expenditure savings of 39.5% are achieved.

Possible Future Work

PAR Improvements

The system implemented in this thesis had positive impacts on electricity expenditure. However it had an erratic effect on the PAR of the household. This means the system benefits the consumer but does not benefit the electricity utility as high PAR consumers force them to rely on peak generation power plants which increase costs. If the system presented in this thesis was to be rolled out to houses in the current network it would need the support of the utility as they would need to broadcast the RTP prices it requires to work. As it stands they would have no motivation to support the adoption of this system. In order to change this, the obvious next step in this project would be to alter it to have a positive effect on PAR. One way would be the introduction of an IBR pricing model to complement the RTP. Based on the result of the typical appliances simulation another possible approach could be to intelligently disable and enable the local renewable system on a day by day basis.

Continue Prototype Development

Further improvements could be made to the nanogrid prototypes. The current prototype consists of a raspberry pi connected to an array of relays on a bread board. If this system is to be mass produced then an embedded solution will have to be designed. This could be a standalone device but to be truly effective it would have to be built into appliances. That way the controller would have true control over the operation of the appliance and would allow for more fine-tuned, appliance specific load scheduling. Mass production of this nature would also reduce the cost of the system thus increasing the savings of any customer that installs the system. With mass production in place scaled testing could also be carried out. The current system is designed with a single household in mind. It consists of one controller managing a single house worth of appliances. If the system scaled well the feasibility of a model with one controller managing multiple houses or a neighbourhood could be examined.

Introduce Local Power Storage

The nanogrid prototype used in this thesis has a battery apparatus connected to it via its relay array. The battery can connect to the inputs and output gateways of the nanogrid in addition to the nanogrids load. It is set up to allow charging from both the grid and other batteries. Making use of this storage capability could improve the load scheduling system by allowing a consumer buy electricity when it is cheap and use it when it is expensive. The addition of local storage would open up new possibilities for methods of reducing household electricity expenditure and PAR.

References

[1] A. Faruqui, D. Harris, R. Hledik, “Unlocking the €53 Billion Savings from Smart Meters in the EU” Energy Policy Volume 38, Issue 10, October 2010, Pages 6222–6231.

[2] B. Nordman, K. Christensen, A. Meier, “Think Globally, Distribute Power Locally: The Promise of Nano-grids,” IEEE Computer, vol. 45, no. 9, pp. 89-91, 2012.

[3] Global Energy Network Institute, Available online: http://www.geni.org/globalenergy/library/articles-renewable-energy-transmission/transmission-north-america.shtml Accessed on 30/04/2015.

[4] National Wind Watch, “Base and Peak Load”, Accessed online: https://www.wind-watch.org/faq-electricity.php, accessed on 30/04/2015.

[5] Office of Electricity Delivery and Energy Reliability, “Smart Grid” Accessed online: http://energy.gov/oe/services/technology-development/smart-grid, accessed on 30/04/2015.

[6] M. Piette, G. Ghatikar, S. Kiliccote, D. Watson, “Design and Operation of an Open, Interoperable Automated Demand Response Infrastructure for Commercial Buildings”, Journal of Computing Science and Information Engineering Vol 9, Issue 2, 2009.

[7] J. Wells, “Consumers Could Benefit from Demand Programs, but Challenges Remain,” United States Government Accountability Office, 2004.

[8] OpenADR Alliance website, http://www.openadr.org/, Accessed 22/04/2015.

[9] J. Vardakas, N. Zorba and C. Verikoukis, “A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms” IEEE Communication Surveys & Tutorials, Vol. 17, No. 1, First Quarter 2015.

[10] B. Alagoz, A. Kaygusuz, and A. Karabiber, “A user-mode distributed energy management architecture for smart grid applications”, Energy, vol. 44, no. 1, pp. 167–177, August 2012.

[11] SEMO website, http://www.sem-o.com/Pages/default.aspx, Accessed 22/04/2015.

[12] SEMO Market Overview 2013, http://www.sem-o.com/Publications/General/SEMO%20Market%20Overview.pdf, Accessed on 30/04/2015.

[13] G. Weisbrod, E. Ford, “Market Segmentation and Targeting for Real Time Pricing”, Proceedings of the Electric Power Research Institute’s Innovative Pricing Conference, San Diego, March, 1996.

[14] W. Hogan, “Time-of-Use Rates and Real-Time Prices”, Harvard Press, August 23, 2014.

[15] K. Herter, “Residential implementation of critical-peak pricing of electricity”, Energy Policy Volume 35, Issue 4, April 2007, Pages 2121–2130.

[16] P. Reiss and M. White, “Household Electricity Demand Revisited” Rev. Econ. Studies, vol72, no.3, pp.853-883, July 2005.

[17] A.H Mohensian-Rad, L. Garcia, “Optimal Residential Load Control with Price Prediction in Real Time Electricity Pricing Environments”, IEEE Transactions on Smart Grid, Vol. 1, No.2, September 2010.

[18] B. Nordman, “Nano-grids: Evolving our electricity systems from the bottom up,” Berkeley National Laboratory, San Francisco, 2014.

[19] Okabe, Yasuo, “QoEn (Quality Of Energy): Routing Toward Energy And Demand Service In The Future Internet “, ICE-IT, Academic Center for Computing and Media Studies, Kyoto University, November 2009.

[20] J. Bryan, R. Duke, S. Round, “Decentralised Control Of A Nanogrid“, Department of Electrical and Computer Engineering, University of Canterbury, 2002.

[21] 802.3at Amendment 3: Data Terminal Equipment (DTE) Power via the Media Dependent Interface (MDI) Enhancements, September 11, 2009

[22] Electronics component problems for Toyota, found online: http://carrep.blogspot.ie/2011/05/electronic-systems-problems-codes-for.html, accessed on 13/05/2015.

[23] M. He, M. Reutzel, X. Jiang, R. Katz, S. Sanders, D. Culler, K. Lutz, “An Architecture for Local Energy Generation, Distribution, and Sharing”, IEEE Energy2030 Atlanta, Georgia, USA 17-18 November 2008.

[24] Emerge Alliance Occupied Space Standard, Available Online: http://www.emergealliance.org/Standards/OccupiedSpace/Overview.aspx , accessed on: 13/05/2015.

[25] NexTek Power System Available online: http://www.nextekpower.com/tech-overview#power-server-module, Accessed on 13/05/2015.

[26] S. Mishra and O. Ray, “Advances in Nanogrid Technology and Its Integration into Rural Electrification in India,” in 2014 INTERNATIONAL POWER ELECTRONICS CONFERENCE, Hiroshima, 2014.

[27] J. Bryan, S. Round and R. Duke, “Distributed generation - Nanogrid transmission and control options,” in 6th International Power Engineering Conference, Singapore, 2003.

[28] B. Nordman and K. Christensen, “Local Power Distribution with Nanogrids,” in International Green Computing Conference, Arlington, 2013.

[29] A. Goikoetxea, J. Maria Canales and R. Sanchez, “DC vs. AC in Residential Buildings: Efficiency Comparison,” in IEEE EUROCON Conference, Zagreb, 2013.

[30] O. Ray and S. Mishra, “Boost-Derived Hybrid Converter With Simultaneous DC and AC Outputs,” IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS , vol. 50, no. 2, pp. 1082-1093, 2014.

[31] R. Adda, O. Ray and S. K. Mishra, “Synchronous-Reference-Frame-Based Control of Switched Boost Inverter for Standalone DC Nanogrid Applications,” IEEE TRANSACTIONS ON POWER ELECTRONICS , vol. 28, no. 3, pp. 1667-1679, 2013.

[32] R. Haroun, A. Cid-Pastor, A. El Aroudi and e. al, “Synthesis of Canonical Elements for Power Processing in DC Distribution Systems Using Cascaded Converters and Sliding-Mode Control,” IEEE TRANSACTIONS ON POWER ELECTRONICS , vol. 29, no. 3, pp. 1366-1381, 2014.

[33] D. Dong, I. Cvetkovic and D. Boroyevich, “Grid-Interface Bidirectional Converter for Residential DC Distribution Systems-Part One: High-Density Two-Stage Topology,” IEEE TRANSACTIONS ON POWER ELECTRONICS, vol. 28, no. 4, pp. 2707-2713, 2014.

[34] I. Cvetkovic, D. Dong and W. Zhang, “A Test bed for Experimental Validation of a Low-voltage DC Nanogrid for Buildings,” in 15th International Power Electronics and Motion Control Conference and Exposition, Novi Sad, 2012.

[35] A. U. Sankar, S. S. Nag and S. K. Mishra, “A Multi-Input Single-Control (MISC) Battery Charger for DC Nanogrids,” in 5th IEEE Annual International Energy Conversion Congress and Exhibition, Melbourne, 2013.

[36] J. Schoenberger, S. Round and R. Duke, “Autonomous load shedding in a nanogrid using DC bus signaling”, in 32nd Annual Conference of the IEEE-Industrial-Electronics-Society, Paris, 2006.

[37] J. Bryan, R. Duke and S. Round, “Decentralized generator scheduling in a nanogrid using DC bus signaling,” in IEEE-Power-Engineering-Society General Meeting Location, Denver, 2004.

[38] J. Mitra and S. Suryanarayanan, “System Analytics for Smart Microgrids”, in PES General Meeting, Minneapolis, 2010.

[39] J. Doyle, D. O’Mahony, “Pricing Negotiation on Nanogrids”, TBP, Dublin, 2015.

[40] Dantzig G, “Linear Programming and Extensions”, Princeton University Press, 1998.

[41] A. Ipakchi, F. Albuyeh, “Grid of the Future”, Power and Energy Magazine Vol.7 Issue.2 March-April 2009.

[42] Natural Resources Canada, “Energy Consumption of Major Household Appliances Shipped in Canada”, http://publications.gc.ca/collections/collection_2013/rncan-nrcan/M141-16-2010-eng.pdf, accessed 23/04/2015.

Appendix A- Scheduling Code

```
# Name problem and define as minimisation problem.
prob = LpProblem("Electricity Expenditure", LpMinimize)

#Need to dynamiccaly create problem variables since they are not known until received from
#loadgrid.Each variable represents an hourly slot for a single appliance. Each PuLP variable
#requires a unique name so they are stored in a 2d array.One dimension is dictated by the
#appliance number (10 in this case) and by hour number. By setting upbound here we
#introduce the maximum allowable power leve as described in chapter 3.
    variablesCreated = 0
    for i in range(0, 10):
        for j in range(0, 24):
            if schedules[i][j] != 0:
                variableName = "Variable"+str(variablesCreated)
                schedules[i][j] = LpVariable(variableName, lowBound=0, upBound=maximums[i])
                variablesCreated += 1

#The first half of equation 9 from chapter 3.
    prob += lpSum(gridPrice[i]*lpSum(schedules[j][i] for j in range(0, 10)) for i in range(0,24))

#The second half of the equation.
    for i in range(0, 10):
        prob += lpSum(schedules[i][j] for j in range(0,24)) == totalLoads[i]

#Run the solver
    prob.solve()

#Scheduling data passed to local renewable energyutilization module from “prob.variables”.
```

Appendix B- Local Renewable Utilization Code

```
#this function enacts the Local Renewable Utilization strategy outlined in chapter 3.
def decisionAlgorithm(self):
    interested = []
    for i in range(0,24):
      if self.loadGrid.schedule[i] != 0:
        # Load the order from the load node as an index and the grid price tuple.
        interested.append((i,self.gridPrice[i],self.loadGrid.nanogridID))
      if self.loadGrid2.schedule[i] != 0:
        interested.append((i,self.gridPrice[i],self.loadGrid2.nanogridID))

    # Order these tuples in order of price. This way we can allocate our renewable energy
    by which slot is most expensive.
    interested.sort(reverse = True, key=lambda slotPrice: slotPrice[1])

    for i in interested:
      index = i[0]
      print(index)
      insufficientPower = 0   # 0 means enough power present to allow access to renewable

# First need to check ahead to ensure assigning a slot renewable energy won't compromise a
future slot. This works because the orders have been sorted so that the most expensive are
assigned slots first.
      if index >= self.hour:
        for j in range(index,24):
          if self.availableRenewable[j] < self.my_dicts[i[2]].schedule[index]:
            insufficientPower = 1
        j=0
        while j < self.hour:
          if self.availableRenewable[j] < self.my_dicts[i[2]].schedule[index]:
            insufficientPower = 1
```

```
          j+=1
      else:
        for j in range(index, self.hour):
          if self.availableRenewable[j] < self.my_dicts[i[2]].schedule[index]:
            insufficientPower = 1

      if insufficientPower == 0:

# If enough, supply renewable power.
        self.my_dicts[i[2]].RGOschedule[index] = "RENEW"

# Need to subtract load from all future values of available renewable
        if index>=self.hour:
             for j in range(index,24):
                    self.availableRenewable[j]=self.availableRenewable[j]-
                    self.my_dicts[i[2]].schedule[index]
             j=0
             while j<self.hour:
                    self.availableRenewable[j]=self.availableRenewable[j]-
                    self.my_dicts[i[2]].schedule[index]
                    j+=1
        else:
             for j in range(index,self.hour):
                    self.availableRenewable[j]=self.availableRenewable[j]-
                    self.my_dicts[i[2]].schedule[index]
# Else supply grid power.
       else:
              self.my_dicts[i[2]].RGOschedule[index] = "GRID"
```

```
# Function that informs nanogrids what their orders are for this hour. Current set up has one central controller and two nanogrids.
def enactDecision(self):
    if self.loadGrid.RGOschedule[self.hour] == "RENEW":
        self.TRIGGERRENEWABLE(self.loadGrid.IPAddress)
        self.renewableLevel = self.renewableLevel - self.loadGrid.schedule[self.hour]
    elif self.loadGrid.RGOschedule[self.hour] == "GRID":
        self.TRIGGERGRID(self.loadGrid.IPAddress)
    else:
        self.TURNOFF(self.loadGrid.IPAddress)

    if self.loadGrid2.RGOschedule[self.hour] == "RENEW":
        self.TRIGGERRENEWABLE(self.loadGrid2.IPAddress)
        self.renewableLevel = self.renewableLevel - self.loadGrid2.schedule[self.hour]
    elif self.loadGrid2.RGOschedule[self.hour] == "GRID":
        self.TRIGGERGRID(self.loadGrid2.IPAddress)
    else:
        self.TURNOFF(self.loadGrid2.IPAddress)
```