Intelligent Control Strategies for Peak Load Management of Domestic Consumers in Developing Nations

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ABSTRACT

The constantly rising demand for electricity in the residential sector can cause blackout problems unless the demand is met. Many demand response programs are discussed in the existing literature, in which the peak load of houses is shifted by managing the time of use of appliances. In these programs, data exchange between supply and demand is required, and achieved by the integration between these programs and smart grid systems. However, in many developing nations conventional electric grids are still used where there is no data exchange. In the present research, intelligent control strategies are proposed to reshape domestic power demand profiles without requiring the grid to be "smart". Two case studies are conducted to demonstrate the effectiveness of the proposed strategies in reducing and shifting the peak demand to off-peak times.

In the first case study, a control strategy is developed in which the operating frequency of domestic water pumps is reduced during peak hours. It is shown that the controller reduces the operating frequency of domestic pumps by 90% during peak hours while increasing their work during off-peak times by 55%. At the same time, the controller does not let the water level drop below 30% of the storage tank's maximum capacity, thereby maintaining an acceptable inside-house water supply pressure that ensures the end-users' water usage comfort. The controller is validated against a MPC controller that reduces the domestic pump operating frequency by 100% but it permits the water level to drop to a critical level that reduces the inside-house water supply pressure.

In the second case study, a fuzzy logic control strategy that operates six home appliances is developed, such that the overall consumption peak current is not exceeded. Additionally, a regional fuzzy controller is used to monitor the overall current consumption of the neighbourhood, helping to control the operation of the fuzzy controllers inside the houses and prevent a regional current consumption overload. The simulations reveals that the fuzzy control strategy shifts 43% of the load from peak hours to other hours while at the same time the occupants' electric usage comfort is preserved.

Cost analysis is conducted to compare the economic feasibility of these control strategies against purchasing new peak diesel generators. If the utility company were to promote the new controllers for pumps in 25,000 houses for free, the utility could avoid investing an extra 773,500US$ for a peak generation of capacity of 2.85MW. On the other hand, the investment avoided by the fuzzy control strategy is approximately 5,000US$ in the case of implementing it in 40 houses. The reduction in peak energy consumption would be approximately 63% and in peak load 52kW.

In order to estimate the power profiles required in the simulations, a power consumption model is developed. The model is validated against actual measurements of domestic power profiles, and the average percentage error between the model and the measurements is found to be 8%. In addition, the model is constructed in Matlab GUI, in order to generalize it and make it easy to use for non-professional people. A survey is conducted to investigate the effect of some socio-demographic factors on domestic power consumption. The multi-regression results show that domestic power consumption is significantly affected by family income and the surface area of homes.

Keywords: Load shifting, pumping work, algorithmic control, fuzzy control, random operation modelling, power modelling, socio-demographic factors.

ÖZ

Konut sektöründe elektrik talepinin sürekli artışı, talep karşılanmadığı takdirde, elektrik kesintilerine neden olabilir. Mevcut literatürde, evlerin puant yüklerinin, elektrikli aletlerin kullanım saatlerini yöneterek, başka saatlere kaydırıldığı bir çok talep tepki programları irdelendi. Bu programlarda, arz ve talep arasında bilgi alışverişine ihtiyaç duyulmakta ve bu programların akıllı şebeke sistemi ile entegrasyonu ile sağlanmaktadır. Bir çok gelişmekte olan ülkede hala konvansiyonel elektrik şebekesi kullanıldığından arz ve talep arasında bilgi alışverişi yapılmamaktadır. Mevcut çalışmada, güç talep eğrilerini tekrar şekillendirmek için şebekenin "akıllı" olmasını gerektirmeyen akıllı kontrol stratejileri önerilmektedir. Önerilen stratejilerin puntı azaltma ve yoğun olmayan saatlere kaydırmadaki etkisini göstermek için iki vaka analizi yürütülmüştür.

İlk vaka analizinde evsel su pompalarının yoğun saatlerde kullanım sıklıklarının azaltıldığı bir kontrol stratejisi geliştirilmiştir. Önerilen kontrol ünitesinin, pompaların çalışma sıklıklarını, yoğun saatlerde %90 azalttığı, yoğun olmayan saatlerde ise %55 artırdığı gösterilmiştir. Kontrol ünitesi bir yandan da, ev içi tesisatında kabul edilebilir bir su basıncına sahip olmak ve konforu bozmamak amacıyla, depolama tankının azami su seviyesinin %30 eşiğinin altına düşmemesini sağlar. Kontrol programının geçerliliği, pompaların çalışma sıklığını %100 azaltan fakat ev içi su basıncınn kritik seviyelere düşmesine izin veren MPC kontrolörü ile kıyaslanarak sağlanmıştır.

İkinci vaka analizinde toplam tüketim puantını geçmeyecek şekilde altı ev aletini çalıştıran bulanık mantık kontrol stratejisi geliştirilmiştir. Ek olarak, toplam mahalli

akımın aşılmaması ve ev içlerindeki bulanık mantık kontrolörlerini çalıştırmak için bir bölgesel bulanık mantık stratejisi kullanılmıştır. Simülasyonlar, bulanık kontrol stratejisinin yükün % 43'ünü yoğun saatlerden diğer saatlere kaydırdığını, aynı zamanda kullanıcıların elektrik kullanım rahatlığının korunduğunu ortaya koymuştur.

Bu kontrol stratejilerinin sağladığı faydalar, puant yükü için dizel jeneratör satın alımı ile kıyaslanarak bir maliyet analizi yapılmıştır. Elektrik kurumu, pompalar ile ilgili kontrol ünitelerinin kullanımını teşvik etmek için 25,000 evde ücretsiz montaj yapabilir. Böyle bir durumda kurum, puant yükte 2.8 MW'lık düşüş sağlayarak dizel jeneratör için gerekli 773,500 dolarlık ek masraftan kaçınmış olacaktır. Öte yandan, bulanık kontrol stratejisinde kaçınılan yatırım, 40 evde uygulanması durumunda yaklaşık 5000 dolarıdır. Puant yükündeki düşüş 52 kW, yoğun saatlerdeki enerji tasarrufu ise yaklaşık % 63 olacaktır.

Simülasyonlardaki gerekli güç eğrilerini tahmin etmek için bir güç tüketimi modeli geliştirilmiştir. Geliştirilen model, evsel gerçek güç eğrileriyle kıyaslanarak, ortalama %8 hata payı ile doğrulandı. Model, Matlab GUI'da tasarlanarak profesyönel olmayan kişiler tarafından da kullanımı kolay bir hale getirilmiştir. Bazı sosyo-demografik faktörlerin evsel enerji tüketimine etkisini araştırmak için bir anket düzenlendi. Çoklu regresyon sonuçları, evsel elektrik tüketiminin, ailelerin gelirlerine ve konut alanlarına bağlı olduğunu göstermiştir.

Anahtar Kelimeler: Yük kaydırma, pompalama işi, algoritmik kontrol, bulanık kontrol, rastgele işlem modellemesi, güç modellemesi, Sosyo-demografik faktörler.

DEDICATION

This thesis is dedicated to the memory of my Mother, who have been the source of inspiration to pursue my doctorate degree. Sadly, she is not around to see my graduation. This is for her.

This thesis is also dedicated to my beloved wife and children who gave me strength, motivation and courage to accomplish the volume of this work .

To all my family, the symbol of love and giving, my friends who encourage and support me, and all the people in my life who touch my heart, I dedicate this research

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I owe quit a lot to my family who allowed me to travel all the way from Palestine to Cyprus and supported me throughout my studies. I would like to dedicate this study to them as an indication of their significance in this study as well as in my life.

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LIST OF ABREVIATIONS

AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Networks
CVaR	Conditional Value-at-Risk
DC	Direct Control
DR	Demand Response
DSM	Demand Side Management
HAN	Home Area Network
HDI	Human Development Index
HEMS	Home Energy Management System
HIL	Hard-in-the-Loop
GUI	Graphical User Interface
ICT	Information Communication Technology
IP	Internet Protocol
MDMS	Meter Data Management System
MIMO	Multi Input Multi Output
MPC	Model Predictive Control
NB-PLC	Narrow Band Power Line Communication
PCBS	Palestine Central Bureau of Statistics
PID	Proportional Integral Derivative
PLC	Power Line Communication
PV	Photovoltaic
RMSE	Root Mean Square Error
SG	Smart Grid

SISO	Single Input Single Output
TOU	Time of Use

LIST OF SYMBOLS

S	Water pump control switch
h_{max}	Maximum water level in rooftop tank (m)
h_{ref}	Refilling water level in rooftop tank (m)
N	Number of samples
E_p	Pump electric energy consumption (kWh)
P_s	Pump start power (kW)
P_{ss}	Pump steady state power (kW)
t_s	Start time (s)
t_{ss}	Steady state time (s)
E_T	Pump total electric energy consumption (kWh)
R	Ratio of pump operation (%)
Q_{in}	Net flow input rate enters the tank (l/s)
Q_{out}	Output flow rate at the exit orifice of the tank (l/s)
Q_d	Domestic water demand (l/s)
Q_p	Pump flow rate (l/s)
Q_{lin}	Flow rate lost in input piping system (l/s)
Q_{lout}	Flow rate lost in output piping system (l/s)
h	Tank water level (m)
R	Flow resistance (N s/m^5)
V	Rooftop tank volume (l)
V_{ref}	Refilling rooftop tank water volume (l)
V_{rnew}	Readjusted refilling rooftop tank water volume (l)
V_{max}	Rooftop tank water maximum volume (l)

h_{peak}	Algorithm needed rooftop tank water level (m)
P_g	Utility grid power factor
P_h	House power factor
I_{rms}	RMS AC current (A)
V_{rms}	RMS AC voltage (V)
P_T	Total power factor
E_{At}	Actual measured total energy (kWh)
E_{Mt}	Model output total energy (kWh)
$\dot{Q}_{pum}$	Pump water flow (L)
T	Sample time (sec)
N	Number of houses
SW	Pump switch statues matrix
ST	Sample time matrix
N_{ol}	Overlapped number of houses
E_{gen}	Power (kW) and energy (kWh) of backup generators
I_{DSM}	Initial investments in DSM program (US$)
LCI_{DSM}	Life cycle investments of DSM program (US$)
$I_{\,gen}$	Initial investments in peak generator (US$)
LCI_{gen}	Avoided life cycle investments of peak generator (US$)
C_{peak}	Electric off-peak tariff (US$)
$C_{off-peak}$	Electric peak tariff (US$)
μ_1 , μ_1	Mean values of hourly average water consumption profile
σ_1, σ_2	Standard deviation values of hourly average water consumption profile

Chapter 1

INTRODUCTION

1.1 Motivation

Energy and the exploitation of energy play an important role in economic and social development (Juaidi et al., 2016). Primary resources, such as heavy oil, natural gas and other conventional energy sources are limited. Fluctuations in reserves and the prices of these resources along with the increased costs of power stations leads to the consideration of new measures for energy efficiency in both developed and developing countries. Energy efficiency can be defined as an applied technique in energy utilization without affecting standards of living in society. Energy efficiency definitely saves investment in constructing and generating electrical energy and consequently enhances the economies of nations (Han et al., 2014). The demand for energy is rising in the residential sector due to increasing usage of electronic and electrical devices. Therefore, it is necessary to manage and control end-users' electricity consumption by redistributing/scheduling its use and providing consistent supply without affecting the comfort level of individuals (Juaidi et al., 2016). Intelligent control strategies can be defined as control approaches that emulate human behaviour and can cope with a large amount of data. These controls can be implemented to reduce the power demand during peak times in any sector. The residential sector is one of the highest power consuming sectors; for example, in Palestine it accounts for 39% of total usage (PCBS, 2015) and in N. Cyprus it accounts for 42% (KibTek, 2012).

1.2 Statement of the Problem

Developing countries or nations are those with a low human development index (HDI), which is an index used to rank countries based on education, life expectancy and country income indicators. Such nations suffer from frequent electric power outages and blackout problems. Solving these problems is a motivation for applying intelligent control strategies using a load approach. One example of a developing country is N. Cyprus, which had 166 electricity outages between September 2013 and September 2014 due to insufficient capacity or failure of generation during peak electricity demand (Yurtsev & Jenkins, 2016). Other examples of such countries are Yemen Republic, which had 52 outages per month in 2010, Pakistan which had 32 outages per month in 2007, and Nepal which had 51 outages per month in 2009 (Černý, 2013). Some nations, such as Palestine, suffer power outages due to insufficient imported electric power from neighbouring countries (Abualkhair, 2007).

Blackouts can occur due to failure in the electricity network, failure in power plants, short circuits or overloaded circuit breakers within the network. Blackouts can also occur due to insufficient power generation to meet peak demand. The implementation of intelligent control strategies to redistribute/schedule domestic electric loads contributes to solving blackout problems.

In order to apply intelligent control strategies, information about end-user power demand profiles is needed. In developed countries, this information is available and achievable due to smart grid systems. Smart grid systems, which have recently been introduced to electricity networks, are based on intelligent digital technologies and communication systems. These intelligent technologies monitor, collect and analyze data about end-users' power demands, and communicate the results with the utility companies through power line communication (PLC), narrow band (NB) PLC, internet protocols (IP), and other communication protocols (Kabalci, 2016). However, in most developing countries, data about domestic power consumption profiles are not available. Therefore, an electric power demand model is needed to estimate these profiles.

The power consumption in domestic buildings is affected by many socio-demographic factors, including family income, building surface area and the number of occupants. The effect of these factors should be recognized and included in the power consumption model.

The problem of blackouts can be solved through the implementation of demand side management (DSM) or demand response (DR) programs. These programs are developed to reduce power consumption during peak demand and increase utility utilization (Jalali, & Kazemi, 2015). When these programs are applied with advanced control technologies, they are integrated with smart grid systems. Unfortunately, in many developing countries smart grids are not available. In these nations conventional grids are still used, meaning there is no data exchange between the end-user and the utility.

1.3 Research Objective and Scope

The main objective of this research is to develop control approaches to enable the handling of the demand curve with the aim of reducing the peak. It seeks to introduce simple intelligent control strategies tailored to conventional grid systems to achieve demand reduction during peak hours. It should be recognized that the comfort levels of consumers must not be compromised, and therefore the devices and the way they operate should be selected carefully.

The research aims to develop simple automatic control systems that can be used with carefully designed demand response programs in countries where conventional grids are in use. It seeks to provide a means to apply a “peak shifting” strategy through intelligent control approaches.

Two case studies are undertaken to observe the technical feasibility of the methodology developed. One focuses on controlling a single device, while the other focuses on controlling a number of devices simultaneously.

1.4 Structure of the Thesis

Chapter 1 introduces the motivation for implementing load shifting control strategies in countries where frequent electric power supply outages occur, and presents the objectives of the research. Chapter 2 introduces the literature review which highlights the problems of applying intelligent control approaches in developing nations. The general concept of the thesis work is introduced in Chapter 3, and Chapter 4 introduces the case of N. Cyprus, where a simple practical controller is introduced to minimize the peak load of the country, by reducing pumping peak power demand. The case of Palestine is covered in Chapter 5 and Chapter 6. Chapter 5 discusses the bottom-up electric power model developed for Palestinian houses. Based on this model, Chapter 6 discusses the control program developed for Palestinian houses. The control program takes a fuzzy control approach to redistributing domestic electrical loads to avoid the blackout problem. Chapter 7 illustrates the environmental and economic impact of control strategies on electrical distribution grids. A summary of the research and suggestions for future work are the subject of Chapter 8.

Chapter 2

LITERATURE REVIEW

2.1 Modelling and Controlling Electrical Energy Consumption

Modelling demand loads and electrical energy consumption is the field of many researchers. Price et al. (1993) introduce the concepts and terminology of modelling approaches with the concentration of dynamic load modelling. Recently developed energy consumption models follow the “top-down” or “bottom-up” approaches. These approaches differ in the hierarchical position of the domestic data required for modelling. The top-down approach assumes houses to be power sinks, and calculates the total power consumption of houses without considering the consumption of the individual partners. The bottom-up approach considers the consumption of the individual partners or groups, then estimates the consumption for the whole residential sector (Swan & Ugursal, 2009).

Physical modelling of end-user power consumption following the bottom-up method depends on the construction of a physical representation of an individual house’s energy demand (Aydinalp-Koksal & Ugursal, 2008). Therefore, a physical model requires measurable data such as environmental conditions, construction materials, occupant numbers and activity levels (Johnston, 2003). Moreover, it requires empirical data from housing surveys, physical building construction and building load operation scenarios. This data gives flexibility in physical modelling through the ability to estimate past, present and future end-user power demand (Wilson & Swisher, 1993).

The accuracy of physical modelling depends on the variables considered in building the model.

Recently many bottom-up physical models have been used in developed countries to estimate the energy consumption of residential houses and the associated CO_2 emissions. Fung et al. (2008) use a residential energy model to study the characteristics of Canadian end-users' energy consumption. They examine the impact of various energy efficiency measures on residential energy consumption, such as increasing envelope insulation, increasing appliance efficiency and increasing heating/cooling system efficiency. Snäkin (2000) uses a model in the South of Finland to investigate the space heating energy required and related greenhouse gas emissions in order to improve the quality and quantity of heating energy and emission data. This model considers fuel and energy statistics, building register data and demographic parameters. Huang and Brodrick (2000) use a bottom-up model to estimate the total heating and cooling loads for the residential and commercial sectors in the USA. Hens et al. (2001) investigate the contribution of the Belgian residential sector's energy consumption to CO_2 gas production, by building an energy model. Taniguchi et al. (2016) simulate a bottom-up model to estimate the Japanese residential electricity demand, considering occupant behaviour, family composition, building surface area and building insulation level. Diao et al. (2017) propose a bottom-up simulation energy model utilizing k-modes clustering and demographic-based probability neural networks to identify and classify occupant behaviour with direct energy consumption outcomes. Subbiah et al. (2017) use an energy consumption model based on building-level, time-dependent demand profiles, appliance usage, appliance energy ratings, the activity of each household member and the shared activities of those members.

Firth et al. (2010) use a domestic energy model for UK housing stock to explore potential solutions to reducing carbon dioxide emissions. Parameters such as average dwelling, space heating, water heating, lights and appliances are considered in their model to estimate CO_2 emissions. Johnston (2003) explores the technological feasibility of reducing CO_2 emissions using a bottom-up model for the energy demand of UK housing stock. Shorrock and Dunster (1997), Boardman et al. (2005), Natarajan (2007) and Levermore (2007) also create models of UK housing stock energy demand. The main purpose of these models is to explore potential scenarios for reducing CO_2 emissions by studying the energy demand of domestic end-users. Although these models are all built for the same purpose, they differ in the complexity and types of parameters and variables considered (Kavgic et al., 2010).

It can be concluded from the literature discussed above that any country that is planning to implement strategic energy auditing programs, CO_2 emission reduction regulations or the successful prediction of future energy demand is in need of an energy consumption model.

2.2 Demand Response Programs

Peak power demand occurs in the grid when most end-users use electricity at the same time. To meet peak power demand, utilities are forced to increase generation by investment in building additional conventional backup generators (iu et al., 2016). Some householders also have to invest in small conventional diesel backup generators to meet their own power demands. However, these solutions are unsustainable because they result in low plant utilization (the ratio of the time the plant is in use to the time it could be in use), which increases the cost of investment and contributes to climate change due to increased carbon dioxide emissions (Apachristos, 2015).

Demand-side management (DSM) is an alternative solution to connecting more conventional backup generators. DSM is a set of interconnected programs to manage end-users to voluntarily change their general consumption of electricity and reduce their load during peak times. This yields better efficiency in the operation of electrical energy systems. The six strategies of DSM are shown in Figure 2.1. Utilities around the world pay for DSM programs because they are generally economical and uncomplicated to acquire compared to conventional backup generators (Setlhaolo & Xia, 2016).

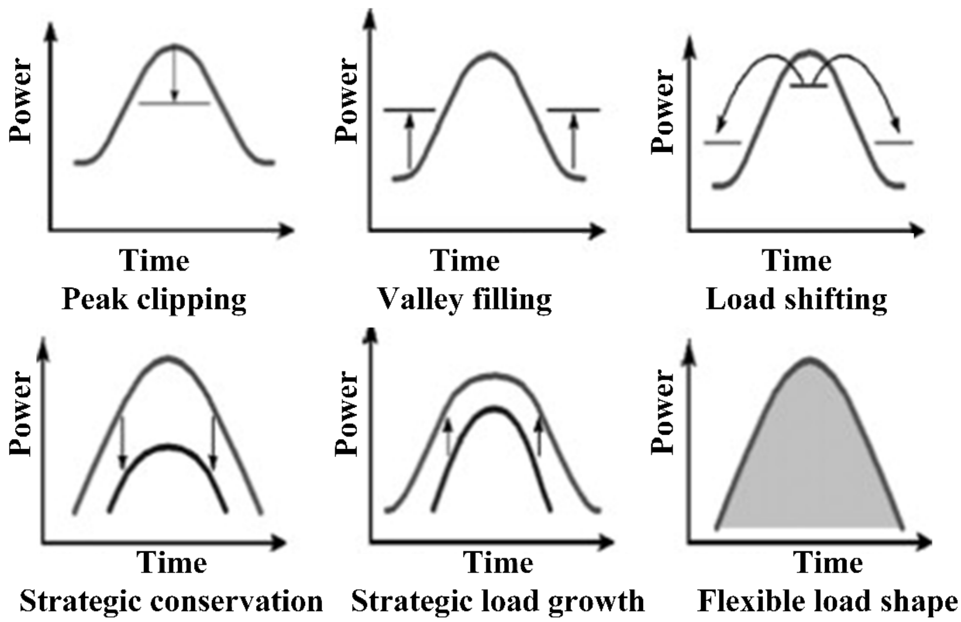


Figure 2.1: DSM Strategies as Displayed in (Harish et al., (2014)

Demand response (DR) is one DSM solution that reduces power consumption during peak demand and increases utility utilization (Jalali & Kazemi, 2015). DR is defined as changes in electricity use by end-users from their general power consumption in response to changes in electricity tariffs at peak and off-peak periods. DR programs can be classified into incentive-based and price-based programs (Safdarian et al., 2016).

In incentive-based programs, a discount on electricity bills is offered by the utility for end-users participating in the DR program. The discount rate is established to allow the utility to access and control the participants' electrical appliances to achieve demand reduction during peak hours. Shahryari et al. (2018) propose an incentive-based program to reduce peak demand in the Spanish electricity market where end-users electric appliances are controlled directly by the utility using load control relays. Usually, DR programs are designed to control the operation of either a group of end-users' electrical loads or to control the operation of a specific electrical load. For example, Tang et al. (2018), Behboodi et al. (2018), Bianchini et al. (2016) and Arteconi et al. (2016) develop DR incentive-based programs to control the operation of devices used in houses for space heating and cooling.

In DR price-based programs, end-users voluntarily modify their power demand profiles based on real-time electricity time-of-use (TOU) tariffs where the price of electricity varies between peak and off-peak times (Ahmed et al., 2017). Similar to incentive-based programs, price-based programs are designed to either manage a group of houses' electrical loads, such as those developed by Bazydło and Wermiński (2018) and Shafi et al. (2018), or control a specific load such as heat pumps, such as those developed by Rodríguez et al. (2018) and Amirirad et al. (2018).

The drawback of incentive-based programs however, is the utility's direct access to switch on and off end-users' electric loads, which intrudes on their privacy and violates their comfort levels. The drawback of price-based programs is that they are based on the end-users' participation in switching their loads on or off following the daily change in tariffs, which is impractical and does not guarantee the achievement of what utilities seek by investing in these programs.

2.3 Utilization of Advanced Control Technologies in DR

Smart grid (SG) systems are based on intelligent control systems, communication protocols and advanced sensing devices such as advanced metering infrastructure (AMI), home area networks (HAN) or meter data management system (MDMS) (Kabalci, 2016). These intelligent technologies monitor, collect and analyze data about customer power demand and communicate the results with the utility.

DR programs integrated with smart grid technologies motivate interested researchers to apply various control approaches and optimization techniques to reduce peak power consumption (Esther & Kumar, 2016b). Wu et al. (2014) investigate a home energy management system (HEMS) consisting of real-time home appliance scheduling, with photovoltaic (PV) cells controlled by fuzzy logic rules to determine the PV charging and discharging time. They also investigate a conditional value-at-risk (CVaR) optimization algorithm to optimize the operation of home appliances. They consider some stochastic variables including expected electrical bills, probable electricity prices and outdoor temperatures. The proposed HEMS decreases the cost of electricity bills and the optimization algorithm schedules home appliance operation near the deterministic schedule.

Bae et al. (2014) depend on information communication technology (ICT) to propose a user-friendly demand side optimization management program. They consider the price of the electric energy supplied by the utility, the electricity bills, the end-users' previous power demand patterns and the rebound peak (the peak that happens because of the DR program). The program is found to reduce electricity bills, avoid the rebound peak and achieve end-user satisfaction. Kunwar et al. (2013) propose a DSM program using artificial neural networks (ANNs) to predict next day loads, and a NSGA II optimization algorithm to optimize load shifting based on electrical pricing. The proposed program reduces electricity bills, maximizes the load factor (which is defined as the ratio of the average load to the peak load during a defined period) and gives end-users freedom to shift their electrical loads.

The first generation ripple control is a central one-way communication load management system (from a distributor and a separate acknowledgment signal to a central transmitter unit over separate communication). The controller is used in many developed countries to shave peak demand. Load management is achieved through an audio signal with a frequency range of 150Hz to 1,350Hz and a voltage level of 5% of the AC voltage of the power distribution grid lines. The frequencies range is selected so as not to coincide with the AC power frequency. The low frequency and the high power values ensure the control signal covers a wide area such that the audio signal passes through the grid transformers. The signal consists of encoded on/off switching bits of 100ms duration. Each encoded signal carries about 50 on/off commands and lasts from several seconds to minutes. In a simple control case, these commands are broadcast to cover the entire area where receivers are configured to switch their connected loads on or off. In an advanced control case, the on/off commands are encoded with addressing maps such that the receivers recognize the addresses of the loads that are to be switched on or off. The ripple control system can be used to control many domestic loads such as water heaters, electric pumps and HAVC systems (Dzung et al., 2011).

Chandran et al. (2016) conduct a comparative study between direct load control (Boolean logic) and fuzzy logic control modifying consumer peak power consumption.

They show that the Boolean logic controller could reduce the consumer peak power consumption at the expense of consumer comfort level, while the fuzzy logic controller could reduce the end-user peak power consumption but preserved the thermal comfort of the consumer. This approach has the capability to include non-deterministic variables such as comfort level.

Zhuan et al. (2013) formulate the scheduling of water pumping as a dynamic optimization problem. Since solving optimization problems needs high computational capacity, the authors use an algorithm that reduces comparative computation time. Wamalwa et al. (2017) formulate a multi-objective optimization problem to minimize the water pumping energy demand and the wear and tear of a hydropower plant pumping system by minimizing the switching frequency of the pumping work. Tang et al. (2014) consider a demand-side management load shifting strategy and save 30% of pumping station electric energy consumption by introducing an optimal control approach. Proportional-integral-derivative (PID) and model predictive control (MPC) approaches are investigated as DR control programs. Abirami et al. (2014) and Li (2010) find that MPC is better than PID in handling multi-input multi-output (MIMO) systems, while the former is better for single-input single-output (SISO) systems. Wanjiru et al. (2016) study MPC of water pumping work by tracking time-of-use (TOU) tariff in Africa, and find that the MPC gives a good result in shifting the pumping work to off-peak hours.

The control algorithms and approaches used in the existing literature require high computational capacity. Thus, they are only suitable for implementation in places where well prepared high computation capacity devices exist, as in pumping stations or utility buildings. However, these control algorithms and approaches are difficult to apply using low computational capacity cost-effective integrated circuits as microcontrollers. These types of integrated circuits are suitable for simple applications such as domestic loads and time-of-use management. Moreover, the work of these control approaches depends on economically costly analogue measurement sensors, which increase the complexity of the control system (Wanjiru et al., 2016). In addition, these sensors need to be handled by professional people.

The proposed DR programs in the existing literature are implemented based mainly on the availability of power, the pattern of consumption of the end-user, the reward strategies of the utilities (such as dynamic tariffs), and the exchange of data between the utility and the end-user. In developed countries, these factors can be easily achieved because of the smart grid communication system. However, they are not available in many developing countries because of the lack of communication systems to provide data exchange between electricity consumers and utility companies. Thus, intelligent controllers integrated with technologies such as KNX/EIB, that provide both measurement and exchange of data, are a promising DR strategy that can be applied in these countries.

2.4 Research Contribution

The present research is concerned with developing novel closed-loop control strategies that modify the domestic demand profile that are especially suited to conventional grids. The strategies aim to reduce the peak power consumption by shifting the operation of a number of domestic electric loads to off-peak hours. In many developing countries this can help avoid blackouts. In addition, the control strategies need to be simple, practical, affordable and implemented using low cost computational technologies. It is important that the strategies suit developing nations which suffer economically. The control strategies should be implemented without requiring modification to the grid or controlled load. This research considers control strategies that differ from those mentioned in the existing literature which require data exchange between the utility and the end-user, by considering the overload current values of the region and in-house circuit breakers as input data constraints for the controllers developed. The direct-control approach is considered in developing strategies that monitor total in-house power demand on a real-time closed-loop basis. They must compensate for the effect of any unexpected change in residential power demand, and continuously avoid blackouts.

In developing these control strategies, information about domestic power consumption profiles is needed. Several energy models have been built to service developed countries, but it is hard to find a model built to service developing nations. Ghedamsi et al. (2016) use a model for distributing and predicting domestic energy demand in Algeria, but in the residential sector, the power consumption profile depends on household loads as well as the nature, culture and socio-demographic factors of the end-user, and for these reasons the model has to be built for a particular country in order to accommodate the power consumption profile of that country. This research develops a power consumption model based on the model for the Algerian residential sector constructed by Ghedamsi et al. (2016). However, this research proposes a model which takes into account the effect of some socio-demographic factors of domestic power consumption.

Chapter 3

METHODOLOGY FOR DOMESTIC LOAD MANAGEMENT

3.1 Introduction

Many developing nations suffer from blackout problems. For example, in 2013 Lebanon and Bangladesh faced averages of 50 and 64.5 electric outages per month, respectively (World Bank, 2018). The matching of power supply to power demand using load management programs that reduce demand or reshape demand profiles contributes to solving the blackout problem.

In developing nations, the direct control approach, utilizing closed-loop control strategies for controllable electric loads, is a suitable solution to match power demand to power supply. Direct control of domestic electrical load is a management approach in which electric loads are switched on or off, either manually or automatically, to postpone their power consumption during peak hours. One crucial issue is that any control approach should ensure adequate end-user comfort. Therefore, the major challenge is to reduce peak power demand by optimizing the operation of domestic electrical loads without affecting end-user comfort.

3.2 Motivation for Using Real-Time Intelligent Controllers

This research concerns developing intelligent closed-loop direct control strategies. These control strategies' purpose is to reshape residential power demand profiles through redistributing the operating times of some power consuming domestic electrical loads over a specified control period.

Factors such as the power rating of domestic appliances, the priority of the loads, and the behaviour and comfort of end-users are considered. It is important that the control strategies' closed-loop designs can measure any instantaneous change in power demand arising from these factors in real time and react accordingly. On the other hand, the design of the control strategies needs to be simple and economically feasible in order to allow policies to be developed by utilities or government bodies.

3.3 The Difference between Classical and Intelligent Control

Both classical and intelligent control techniques are commonly used for DC load management approaches. Classical controllers (also called mathematicians controllers) such as traditional single-input single-output controllers (PID, lead-lag compensators), or modern multi-input multi-output controllers (using the state feedback approach) are efficient and functional when the system dynamics are mathematically well defined, i.e. the system transfer function is well known. These controllers need the system to either be linear or approximate a linear dynamic system. Intelligent control approaches (also called lazymans approaches) such as fuzzy logic or algorithmic controllers, abstractly model the behaviour of the system, therefore the internal dynamics of the controlled system need to be abstractly known.

Domestic power demand is very difficult to fully model mathematically because of the complexity of the non-deterministic variables that affect demand. Power demand in domestic homes can be affected by inside-house factors such as the socio-demographic factors, number and availability of the family members, and the area of the house, and

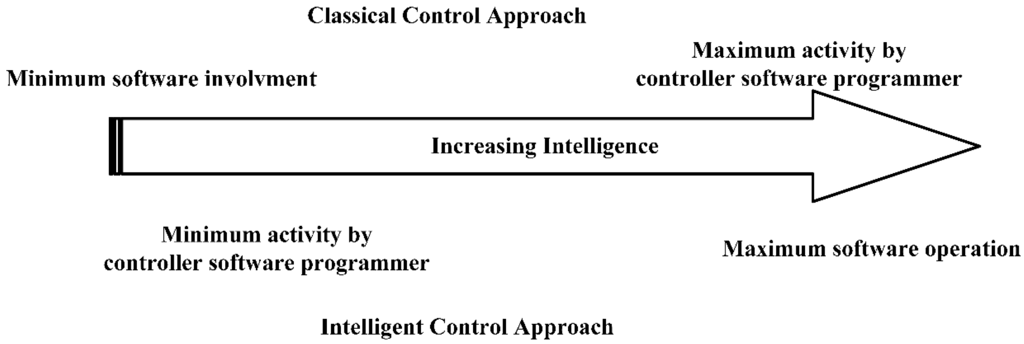


Figure 3.1: Differences between Intelligent and Classical Control Approaches

outside-house factors such as the environmental conditions and time of year. For these reasons the computation should be left to the controller software (see Figure 3.1) and the controller should be flexible enough to adapt to each house individually; these are the characteristics of intelligent controllers. Table 3.1 summarizes the differences between classical and intelligent control techniques.

Table 3.1: The Differences between Classical and Intelligent Control Approaches

Classical control approaches	Intelligent control approaches
Functional if the controlled system is mathematically well defined	Functional if the controlled system is mathematically or abstractly well defined
The controlled system should be linear or approximately linear	Works efficiently with linear and nonlinear systems
Minimum control software involvement	Maximum software operation
Minimum activity by controller software programmer	Maximum activity by controller software programmer

3.4 Closed-Loop Intelligent Control of Domestic Electrical Loads

It is possible to design closed-loop intelligent control systems for domestic electrical loads in order to actuate them with peak hours taken into consideration. In the closed-loop controller shown in Figure 3.2, the total consumed current in a house is measured and compared with the desired limiting peak current value $r(t)$. Controlling actions are taken to minimize the error $e(t)$ between the system reference input $r(t)$ (designer predefined inside-house limiting current) and system output $m(t)$. The value of this error $e(t)$ determines whether the peak power demand is reached. A positive error value means that peak power demand is reached, in other words the inside-house consumed current $m(t)$ is exceeding the predefined inside-house limiting current $r(t)$. Negative or zero values mean that there is no peak demand.

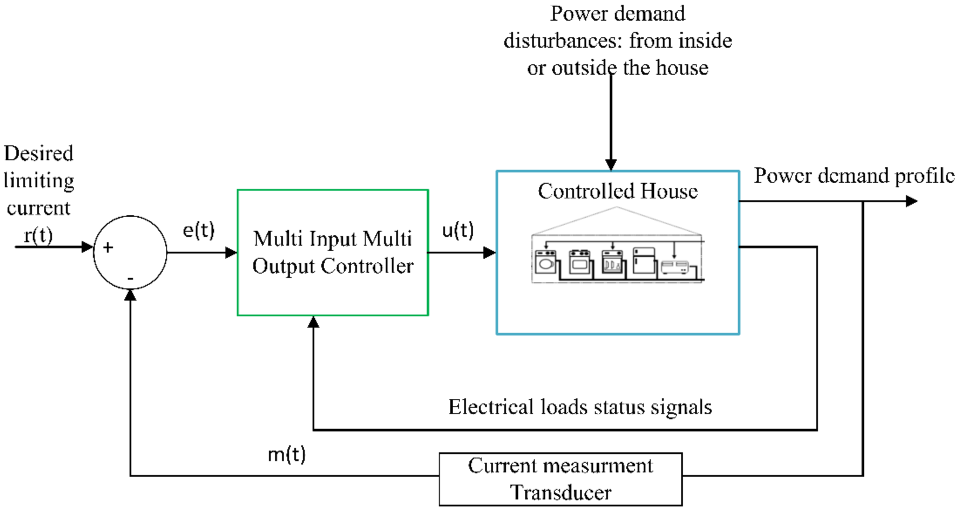


Figure 3.2: Block Diagram of Domestic load Controller

The domestic loads' on/off statuses should be acquired by the controller on a real-time basis. These statuses and the value of the error determine the domestic load controller output switching on/off signal $u(t)$. For example, at a particular moment, if the error value indicates that the peak exists and one of the controllable loads statuses is on, then the controller output switches off this load.

3.5 Direct Control Strategy for Load Reduction

The flow chart shown in Figure 3.3 describes the steps for developing the proposed intelligent domestic load control strategies. The details of these steps follow.

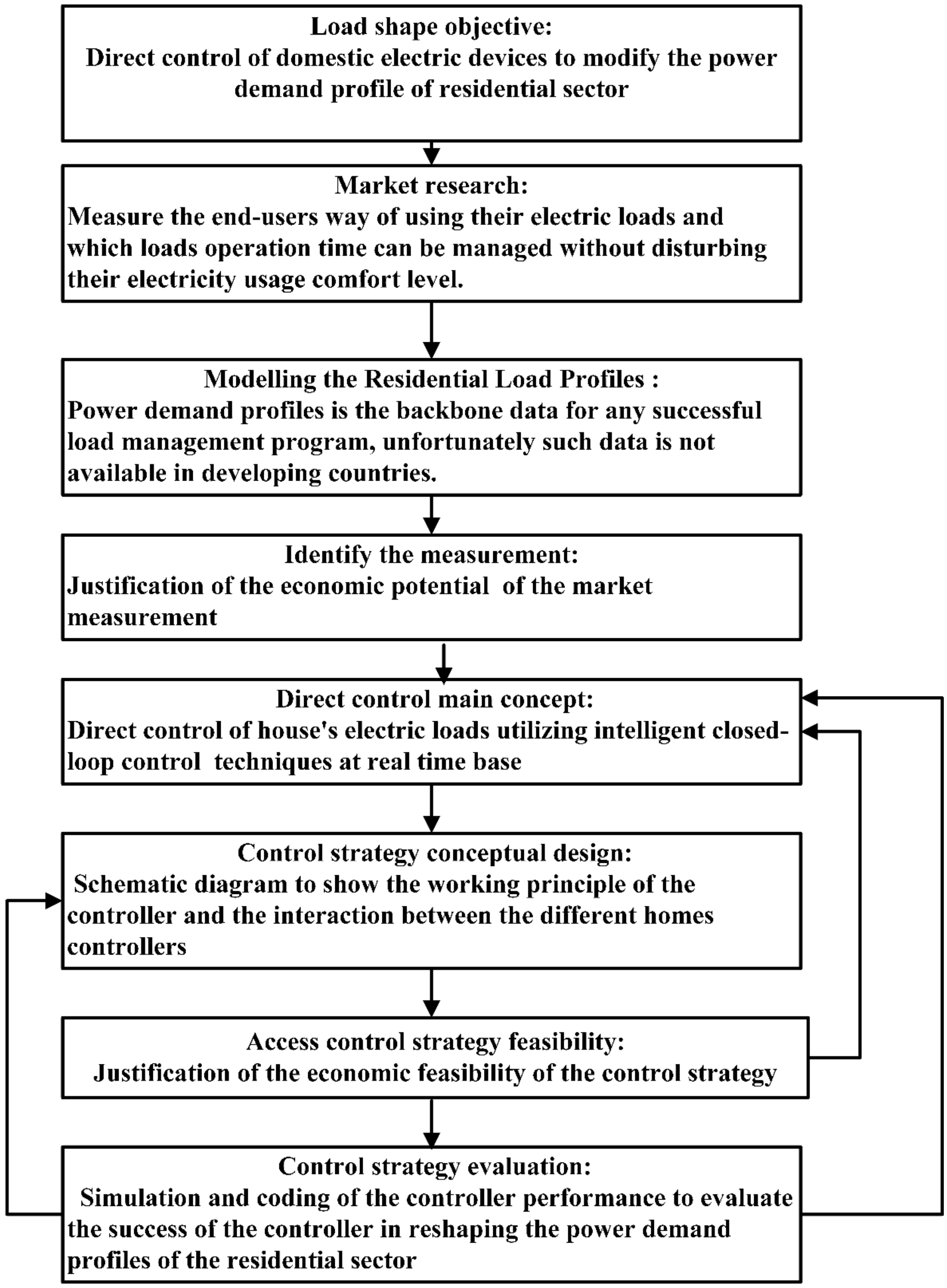


Figure 3.3: Steps for Developing the Control Strategy

3.5.1 Utility Load Shape Objective

It is desirable to modify power demand profiles of the residential sector in countries where a conventional electric grid system is used. This is needed especially during peak times when there is the possibility of power shortages. A well-developed domestic load control strategy can help shift the peak load of each house to off-peak times resulting in a total reduction of demand during peak hours. Figure 3.4 and the mathematical equations below represents the assumed utility load shape objectives.

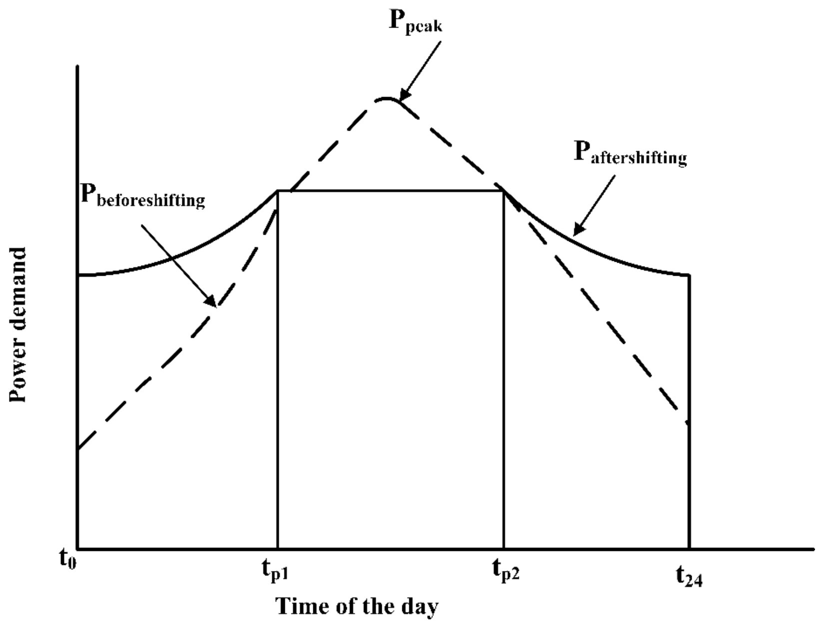


Figure 3.4: Load Shifting Model

The utility assumed objective: $\sum_{i=0}^{24} P_{(aftershifting)i} \times t_i = \sum_{i=0}^{24} P_{(beforeshifting)i} \times t_i$ is under the following power demand constraints:

$$P_{(aftershifting)i} = P_{(peak)i} \; \forall \; t_{p1} \rightarrow \; t_{p2}$$

$$P_{(aftershifting)i} \geq \; P_{(beforeshifting)i} \; \forall \; t_0 \rightarrow \; t_{p1}, \forall \; t_{p2} \rightarrow \; t_{24}$$

$$P_{(aftershifting)i} \leq \; P_{(peak)i \; \forall \; t_0 \rightarrow t_{p1}, \forall \; t_{p2} \rightarrow t_{24}}$$

where, $P_{aftershifting}$ is the power demand after load shifting, $P_{beforeshifting}$ is the power demand before load shifting, and P_{peak} is the peak power demand.

3.5.2 Modelling Residential Load Profiles

The backbone information needed for any successful load shifting control strategy is the power consumption profiles of the targeted sector. This information is not available in many developing countries. Therefore, a bottom-up power consumption model at the level of domestic electrical loads is needed to estimate domestic power consumption profiles. The model should aggregate power profiles based on the operational scenarios of all the expected domestic electrical loads for a typical house in the residential sector. Electricity consumption is affected mainly by customer behaviour and load power capacities. This effect can be translated into other operating scenarios for the devices, and the model can acquire any change in power consumption. The model should be validated by comparing its outputs with actual power consumption measurements for the associated loads.

3.5.3 Market Research and Identification of the Measurement

A way to measure the power profiles of a sample of houses is required. These profiles can be analyzed, along with a questionnaire, to determine the typical electric loads of end-users, and the shifting priorities of these loads that need to be considered in the load control strategy. It is important to design the control strategy in such a way that the end-users' electrical usage comfort level is not significantly disturbed. Information about the socio-demographic factors of power demand is also required. The information gathered from the analysis is used to design a control strategy for reshaping the domestic power consumption profiles while preserving end-user comfort.

It is essential for the utility load shape objective to be achieved with a technically and economically feasible control strategy. In other words, the control system should be implemented using simple, practical, technically available, and economically and computationally low cost technologies.

3.5.4 Direct Control Main Concept

The control strategy depends on the direct and automatic management of the operation times of the controllable domestic electric loads, taking an intelligent real-time closed-loop control approach. In other words, neither the end-users nor the utility are required to interfere in the schedule or change the operating times of the loads. Furthermore, the closed-loop and real-time design of the control strategy must compensate for any variation in power consumption due to any non-deterministic variable such as the end-users' electricity use behaviour.

3.5.5 Control Strategy Conceptual Design

The conceptual design of the control strategy in this research is shown in Figure 3.5. The strategy consists of one regional controller and several inside-house controllers. The inside-house controllers monitor the total consumed current of the house and keep its value below a predefined reference value. If the current consumed exceeds the reference current the inside-house controller is activated to shift the operation time of the controllable domestic loads, such as washing machine, dishwasher, electric pump, lighting system, electric water boiler and refrigerator. This way, the inside-house controller prevents the house peak load exceeding a predefined limit. The region controller monitors the region's main circuit breaker and the consumed currents of each house within the region to prevent the region's peak load exceeding a predefined limit. If the regional current exceeds a predefined value, the region controller sends messages containing the values of the reference current to each house in the region. The region controller determines each house's reference current value relative to the value of the consumed current of that house. Houses with high current consumption receive low reference current values.

The joint operation of the region and the inside-house controllers results in smoothing the power demand profile of the houses by shifting the demand to off-peak times. Accordingly, the country's peak power is reduced by the control strategy.

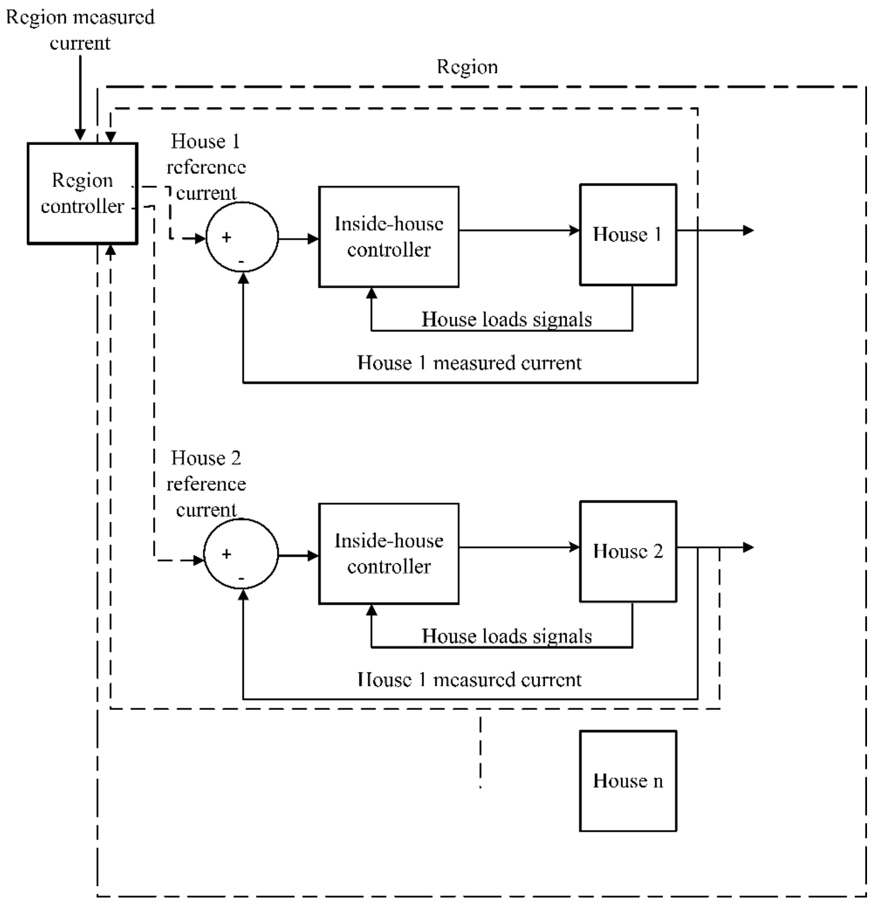


Figure 3.5: Control Strategy Conceptual Design

The control strategy can be used to control the operation of a single domestic load, or it can be used to manage the operation of multiple houses' electrical loads. The proposed control strategy can perform its work independently at the level of each house individually to avoid local house peak power demand. It can also work as a joint controller to avoid regional peak power demand.

3.5.6 Access Control Strategy Economic Feasibility

Utilities usually invest in conventional diesel backup generators to meet peak loads. The purchasing and running costs of these generators are very high compared to investment in a control strategy such as that proposed by this research. Therefore, the proposed control strategy can benefit both utilities and end-users. The utilities benefit by reducing or eliminating the economically high cost investment in conventional backup generators to meet peak power demand, and end-users benefit by reduced electricity bills and the off-peak tariffs offered by the utilities to motivate them to implement the control strategy.

3.5.7 Control Strategy Evaluation and Hardware Implementation

The proposed control strategy can be implemented as a part of DSM policy. The utility can motivate end-users to install these controllers for free in their houses and offer them different electric tariffs to reduce their electricity bills. The implementation of the policy might not be granted, because not all end-users are interested in reducing the utility's peak and may think that the amount by which the electricity bill is reduced is not worth it.

The control strategy developed could be implemented as a compulsory program. However, the work of these controllers depends on sensing devices that sense, in real-time, the running states of electrical loads and instantaneous consumed current. It also depends on switching devices on and off when required, as shown in Figure 3.6. Therefore, to install these controllers, houses would have to be equipped with switching devices.

In newly constructed, modern houses the availability of intelligent technologies and automation networks makes the implementation of controllers reliable. Whereas, in old houses, controllers can be installed by adding simple and low-cost interfacing electric devices. The interface devices could be switched simply using electric relays (see Figure 3.7). If utilities intend to include these controllers in their future plans, it is recommended they advise the owners of newly constructed houses to install modern automation networks.

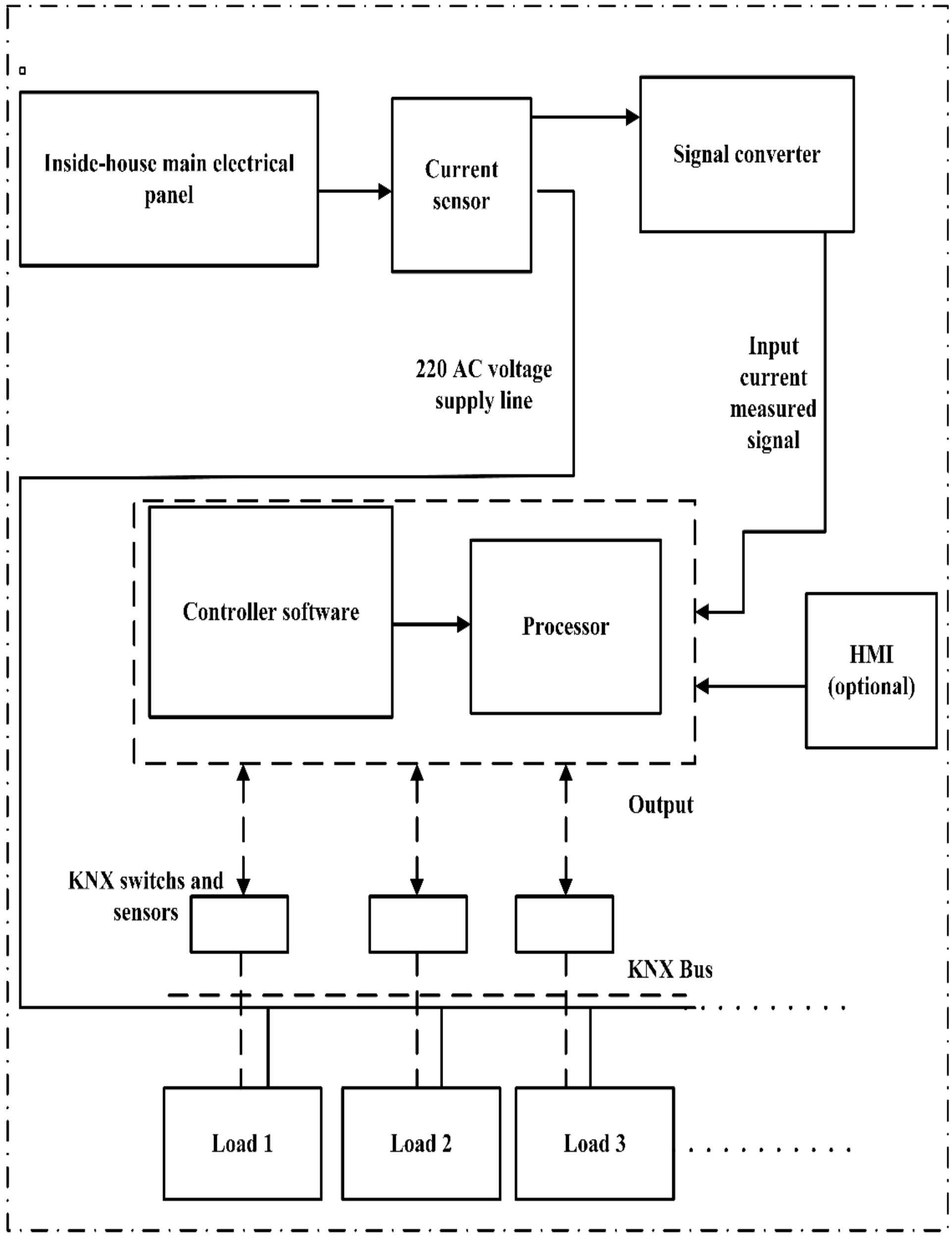


Figure 3.6: Control Strategy Hardware Design

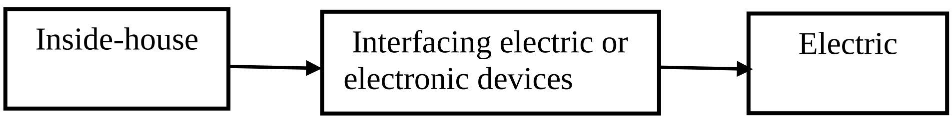


Figure 3.7: Old House Modification Technology

3.6 Matlab/Simscape Toolbar

The Matlab/Simscape toolbar is used to develop the mathematical simulation models needed to construct the proposed control strategies and power demand model. Simscape is a powerful tool for creating models of physical thermal, electrical, hydraulic and electronic systems in the Simulink environment. Within Simscape it is easy to interface between systems. The Matlab environment allows the development of various types of classical and modern control systems and interfacing the controller directly to the model developed. Moreover, it is possible to join the Simulink environment and code-programming in order to deploy the models to other simulation environments such as hardware-in-the-loop (HIL) simulation. Simscape supports C-code generation (Mathworks, n.d.). All these characteristics make the Matlab/Simscape environment different from other analysis tools such as Open DSS, Gridlab-D, OpenWaterAnalytics/EPANET-Matlab-ToolKit etc.

3.7 Chapter Summary

The general aim of this research is to manipulate and reshape residential sector power demand profiles in developing countries where conventional grids are still in operation by applying intelligent control strategies that use a load shifting technique at the domestic level.

Chapter 4

DOMESTIC WATER PUMPING LOAD CONTROL STRATEGY

4.1 Introduction

The water-energy nexus is defined as the energy consumed in the extraction, purification, delivery, heating or cooling, treating and disposing of water. Water services consume a high percentage of a country's total power demand. For example, Saudi Arabia uses about 9% of its power for water pumping and desalination, United Arab Emirates uses about 22% for desalination and Turkey uses about 90-110GWh for wastewater treatment (Siddiqi, 2011). United States on-farm operations consume 1% of the total power consumed in the country (Miranowski, 2005). Therefore, water-energy nexus management has a large effect on energy conservation. Chen et al. (2012) investigate the nexus between power consumption and water use in developing countries, and show that a city's power consumption and the energy used for water services are directly connected. Talebpour et al. (2014) address the water-energy nexus by measuring the energy intensity needed to serve micro-components (such as WCs, dishwashers, washing machines, etc.). Vieira et al. (2016) study the water-energy nexus in Brazil, and show that water services (pumping) increases end-users' electrical energy consumption.

Water-energy nexus management in residential buildings has big implications for conserving continuous potable water supplies, as well as reducing electrical energy demand. Frequent electricity outages and shortages of water can force occupants to invest in various types of water storage devices, such as rooftop or ground-level tanks (Malik, 2002). Where there are water shortages, there is also low water supply pressure in main pipes, so water is pumped from ground level to roof level by means of electric pumps (Wanjiru et al., 2016). The electric water pumps used in houses cause extra electricity demand, and pumping usually takes place without consideration of peak electricity demand time.

The purpose of this chapter is to explore the contribution of the currently existing domestic pump-storage system in N. Cyprus to increasing peak electricity demand and introduce water level modification control approaches to shifting the pumping work to off-peak hours.

4.2 Methodology

Two control approaches are proposed and compared in this chapter, to minimize the pumping work during peak hours. The first approach depends on readjusting the refilling of the rooftop tank to a lower level than currently. The second approach depends on a control algorithm that tracks the rooftop tank water level, the electricity and water supply and the peak power demand times. The second approach requires an additional electric level float switch to be installed in the rooftop tank.

4.3 Domestic Pump-Storage System

N. Cyprus buildings consist of houses with an average surface area of 172.9m^2. Single houses are the most popular building type, comprising about 68% of Cyprus building stock (Panayiotou, 2010). Multi-storey buildings are the second most common type, with most consisting of two to four floors, and each floor having one to four apartments.

In order to overcome the problem of intermittent water supply and electricity shortages. Households install 2,000 litre ground-level and 1,000 litre rooftop non-pressurized, horizontal cylindrical storage tanks. These tanks provide indoor house water through gravity (Yurtsev & Jenkins, 2016). A centrifugal 1hp electric pump is typically used by each house to pump water between the two tanks (Yurtsev & Jenkins, 2016). The water level in the rooftop tank is determined by an electric float switch (Figure 4.1). The pump is turned on when the water level in the rooftop tank drops below (h_ref), and the pump is turned off when the water level reaches (h_max). To prevent flooding from the ground-level tank, a mechanical float switch closes the water supply when the tank is full.

The pump-storage system shown in Figure 4.1 is a popular system used currently in N. Cyprus buildings. The different heights of buildings affect the pump water flow, due to the increased friction induced by the additional pipes and pipe fittings. Mathematical and Matlab models have been developed to test pumping under variable conditions, and how these conditions affect the number of times the pump is turned on during peak demand hours.

4.4 Matlab Model

A Matlab simulation/Simscape model is constructed, as shown in Figure 4.2, to measure the variation in flow produced by the pump due to different pump-storage system heights and different operating conditions, such as a drop in the electricity grid supply of AC voltage or an increase in water demand. The model is developed to test control approach performance in various water pumping scenarios.

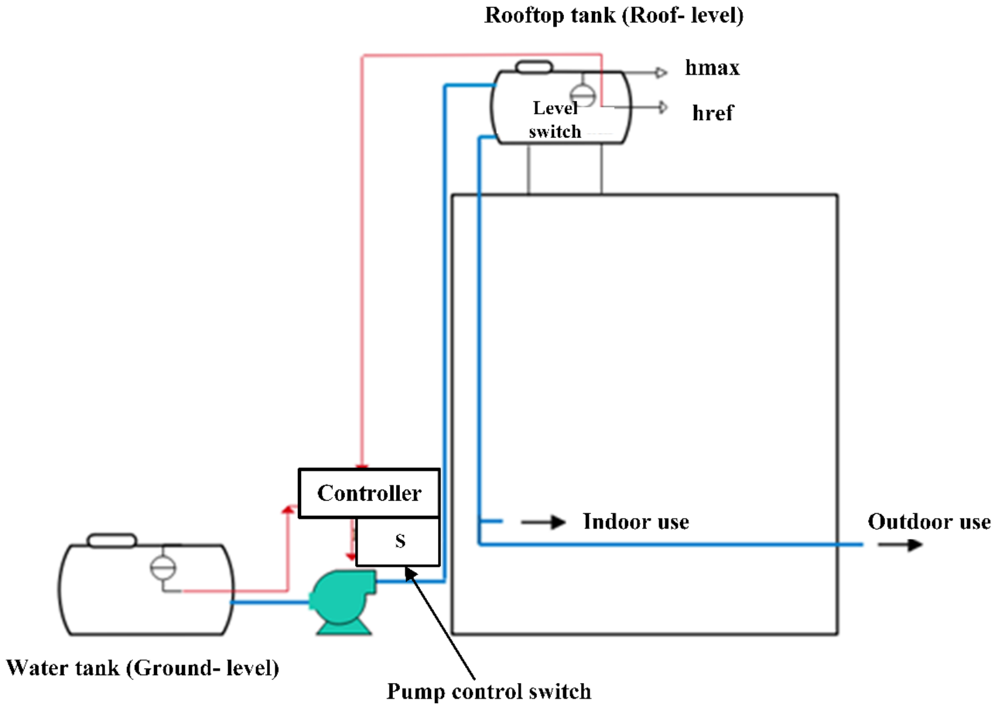
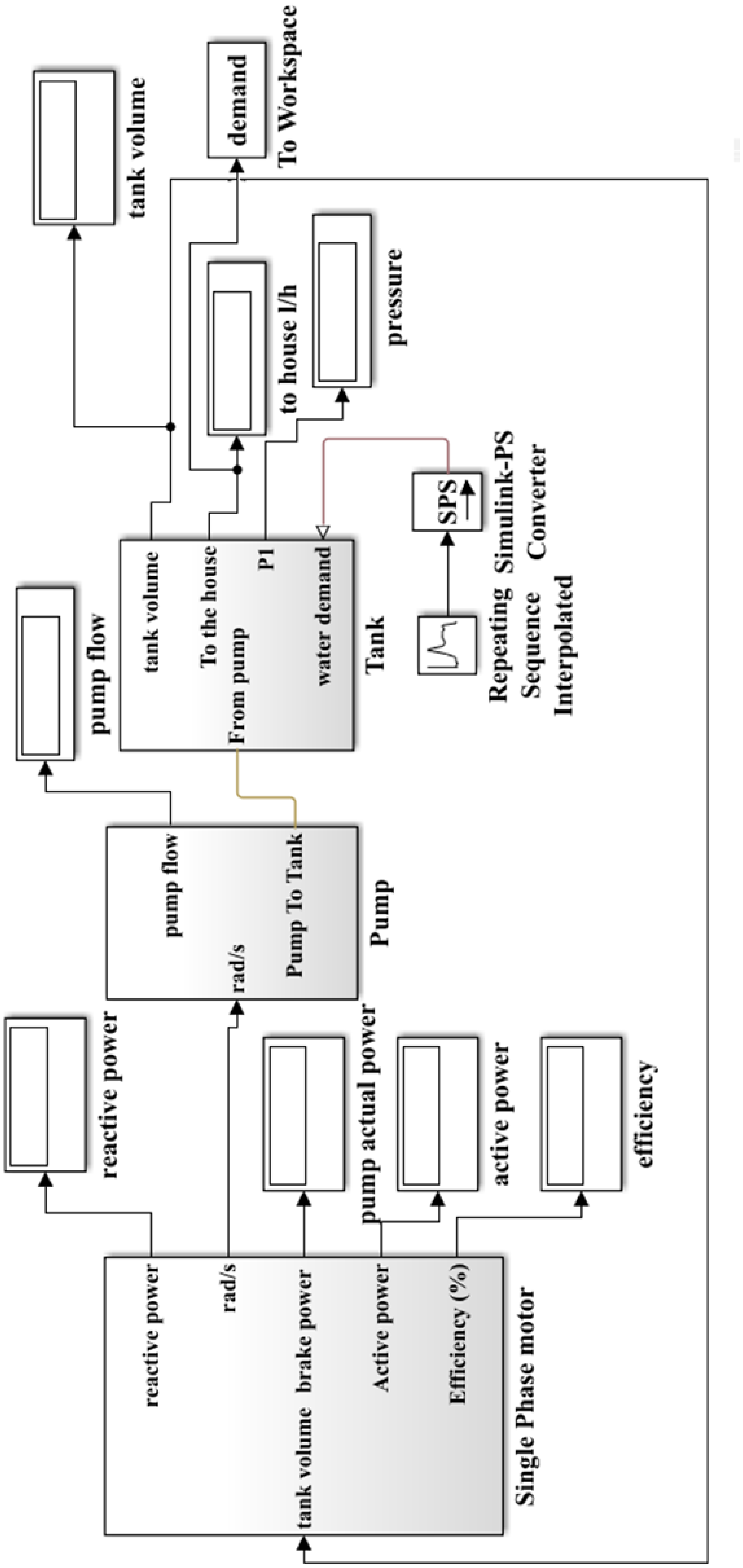
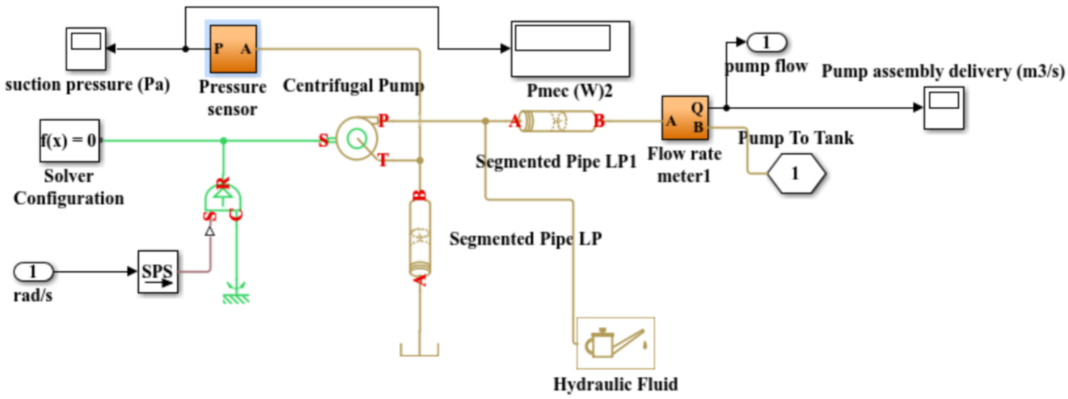


Figure 4.1: Schematic Diagram of a Popular Domestic Pump-Storage System in N. Cyprus

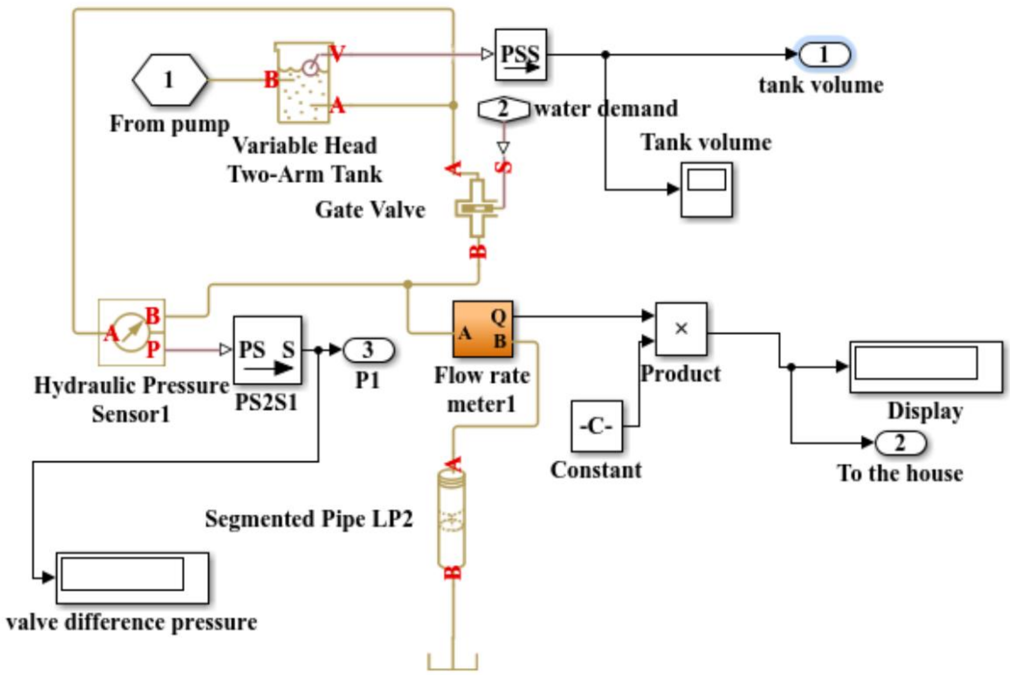
The most popular domestic water pump type used in N. Cyprus is a fixed speed, 1hp, 2,850RPM centrifugal pump. The pump's characteristic flow, head and brake power curves, according to the Elettropompe (2016) catalogue, are inserted as a spline interpolation parameter vector in the pump Matlab block (Figure 4.2b). The pipe lengths and friction coefficients at the start are selected to suit a house with a height of 4m. These parameters are varied to test the effect of these parameters on control approach performance. The water demand is controlled using a water valve connected to the output port of the 1,000 litre storage tank (Figure 4.2c).


tank volume
demand
To Workspace
to house l/h
pressure
pump flow
tank volume
To the house
P1
From pump
water demand
Tank
SPS
Simulink-PS
Converter
Repeating
Sequence
Interpolated
pump flow
rad/s
Pump To Tank
Pump
reactive power
pump actual power
active power
efficiency
reactive power
rad/s
brake power
Active power
Efficiency (%)
tank volume
Single Phase motor

(a)



(b)



(c)

Figure 4.2: Physical Model of the Domestic Pump-Storage System Using the Matlab Hydraulic Library: (a) Pump-Storage System, (b) Water Pump, (c) Rooftop Storage Tank

4.5 Mathematical Model

4.5.1 Water Pump Power

The time horizon selected for one pumping work day is from 0 to 24 hours with a sampling time n of 1 second. The sample number is:

$$\text{n} \in \text{N} \quad \text{n} = 1,2, \ldots \ldots 86400 \tag{1}$$

The pump operation is controlled by switch S, the state of which at any sample time $S\ (n)$ is given by:

$$S(n) \in \{1,0\} \;\; 1\text{: "on", } 0\text{: "off"} \tag{2}$$

The pump energy consumption E_p at each sample time, depends on the pump start power P_s (kW) and the pump steady state power consumption P_{ss} (kW):

$$E_p(n) = (P_s t_s + P_{ss} t_{ss})/3600 \qquad (\text{kWh}) \tag{3}$$

The total pumping energy E_T over the required time horizon is given by:

$$E_T = \sum_{n=1}^{N} E_p(n)\, S(n) \qquad\qquad (\text{kWh}) \tag{4}$$

where,

t_s: start time in seconds, and

t_{ss}: steady state time in seconds.

The ratio R of the number of pump operations during peak demand time to off-peak time is:

$$R = \frac{\sum_{j=peak\ start}^{k=peak\ end} S(j)}{\sum_{n=1}^{N} S(n)} \tag{5}$$

4.5.2 Rooftop Tank Capacity

The volume change rate in the rooftop storage tank with respect to time is given by:

$$\left.\begin{aligned} \frac{dv}{dt} &= Q_{in} - Q_{out} \\ Q_{in} &= Q_p - Q_{lin} \\ Q_d &= Q_{out} - Q_{lout} \\ Q_{out} &= \rho g h/R \end{aligned}\right\} \tag{6}$$

where,

$\frac{dv}{dt}$: tank volume change rate (l /s)

Q_{in} : net flow rate that enters the tank (l /s)

Q_{out}: output flow rate from the tank (l /s)

Q_d : in-side house water demand (l /s)

Q_p : pump flow rate (l /s)

Q_{lin}, Q_{lout}: lost flow rates due to input and output piping systems

h : tank water level (m)

ρ, g : water density and acceleration due to gravity, respectively, and

R : resistance to Q_{out} due to water valves and pipes (N s /m^5).

The flow rate values can be measured and monitored using the Matlab model shown in Figure 4.2. From Eq. (6) it can be seen that the water demand Q_d is affected by the height of the water in the tank.

By discretizing Eq. (6), the tank volume V in litres at each sample time difference is given by:

$$V(n+1) = V(n) + S(n)\,\Delta t\,(Q_p - Q_{lin}) - \Delta t\,(Q_d + Q_{lout}) \qquad (7)$$

where $\Delta t = t(n+1) - t(n)$ is equal to 1 second.

The pump is a fixed displacement type, therefore the pump flow rate Q_p is constant unless the efficiency of the pump decreases. Q_{lin} and Q_{lout} are constants for each water pipe network installation. Water demand Q_d is the estimated inside-house daily water demand of a single house in N. Cyprus.

4.5.3 First Control Approach

This approach is based on readjusting the water level h_{ref} in the rooftop tank to a lower level than the current control scheme h_{rnew} . The water volume in the rooftop tank at any sample interval n in the current water level control scheme is bounded, as shown in Eq. (8).

Based on this readjustment, the new water volume boundaries in the first control approach become:

$$V_{ref} \leq V(n) \leq V_{max} \quad (8)$$

$$V_{rnew} \leq V(n) \leq V_{max} \quad (9)$$

where,

$V_{ref} = Ah_{ref} \quad (l)$

$V_{max} = Ah_{max} \quad (l)$

$V_{rnew} = Ah_{rnew} \quad (l)$

A: is the area of the rooftop tank (m^2).

If the water volume in the tank is below V_{rnew} , the pump is turned on, as long as the ground-level tank is not empty of water. When the water volume reaches V_{max} the pump is switched off. V_{rnew} is less than V_{ref}, which results in a decreasing frequency of the pump's on/off cycle, reducing the number of pumping times throughout the control time horizon.

4.5.4 Second Control Algorithm Approach

The second control algorithm needs an additional floating switch installed in the rooftop tank, as shown in Figure 4.3, adjusted to water level h_{peak}.

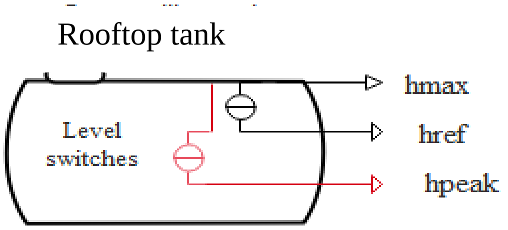


Figure 4.3: Modification Required for the Water Level Algorithm Approach

During off-peak hours, the boundary of the water volume in the tank is constrained by Eq. (8), while during peak hours the boundaries are given by:

$$V_{peak} \leq V(n) \leq V_{max} \tag{10}$$

where, $V_{peak} = Ah_{peak} \times 1000 \quad (l)$

The peak pumping times are determined by the value of $V_{peak,}$, which is less than V_{rnew}. V_{peak} should not drop below a value that decreases the domestic water supply pressure. The algorithm shown in Figure 4.4 tracks the electricity peak times, either based on predetermined statistical data or real-time data via a signal from smart meters if available.

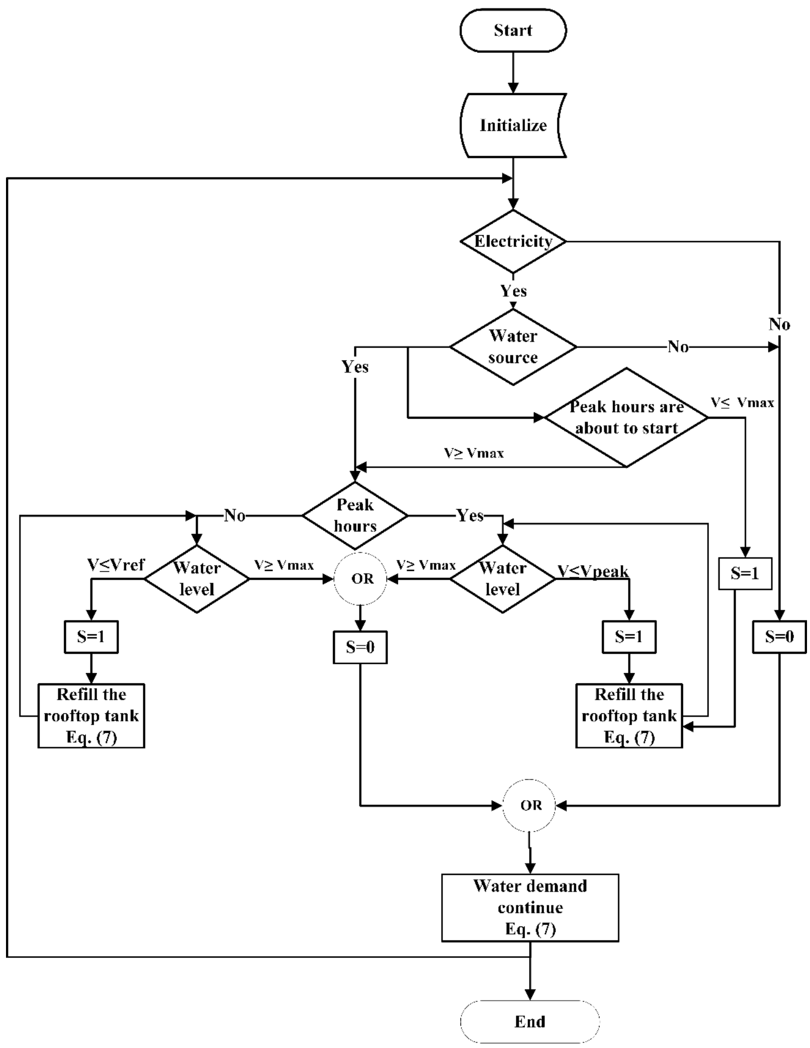


Figure 4.4: Second Control Algorithm Approach

The control algorithm reduces the peak pumping work compared to both the existing and first control approaches, and at the same time satisfies the daily domestic water demand. The algorithm starts the pump just one time at the beginning of peak hours to ensure that the rooftop tank is full before entering the peak period.

Table 4.1:Water Level Modified Control Algorithm

```
Input, Q_d, Q_in, Q_out, Q_lin, Q_lout
Initialize, j → 1:N
if electricity on
        if floor water tank is not empty
        If peak hours are about just to start and tank volume ≤ v_max
                S(j) = 1
                V(n + 1) = V(n) + S(n) Δt (Q_p − Q_lin) − Δt (Q_d + Q_lout)
        end
            if peak time
              if tank volume ≥ v_max
                S(j) = 0
              elseif tank volume ≤ v_peak
                S(j) = 1
                V(n + 1) = V(n) + S(n) Δt (Q_p − Q_lin) − Δt (Q_d + Q_lout)
              end
            else (off − peak time)
                if tank volume ≥ v_max
                S(j) = 0
                elseif tank volume ≤ v_ref
                S(j) = 1
                V(n + 1) = V(n) + S(n) Δt (Q_p − Q_lin) − Δt (Q_d + Q_lout)
            end (cheking peak time)
        else ( water tank is empty)
            S(j) = 0
        end (checking water source)
else (electricity off)
S(j) = 0
V(n + 1) = V(n) + S(n) Δt (Q_p − Q_lin) − Δt (Q_d + Q_lout)
end (checking electricity)
Repeat j
```

The algorithm shown in Table 4.1 has low computation costs, which helps when implementing it using low cost integrated circuits.

4.6 Case Study

A single family house in N. Cyprus is considered in this research. The surface area is 150m^2 and the house has four occupants. The pump-storage water system in the house consists of a horizontal cylindrical rooftop water storage tank with a volume of 1,000L, a ground-level storage tank with a volume of 2,000L and a 1hp, 2,850RPM fixed speed centrifugal water pump. Currently, two float switches are employed in the existing water level control system, one inside the tank at ground level and the other in the rooftop tank to control the cyclic operation of the pump. It is assumed that the water refilling takes place in the rooftop tank between volumes of 950L and 1,000L. The purpose of the switch in the ground-level tank is to stop the operation of the pump when the tank runs out of water.

4.6.1 Water Demand

The estimated hourly water demand profile, shown in Figure 4.5, is used as an example with which to run the control algorithm. It should be noted that the control algorithm is capable of working under any water demand. The profile coincides with the findings of Panayiotou et al. (2010) who analyse the water demand of three urban areas in Cyprus (Nicosia, Limassol and Larnaca). They find an average daily water consumption of 40L/h for the Larnaca area. The water consumption peaks coincide with the findings of Willis et al. (2011), and the daily average water consumption per person is similar to the estimations of Memon et al. (2014) who estimate the average water consumption in the UK to be 150L per person per day. Based on the findings in the above literature, the typical water demand curve for N. Cyprus can be estimated as shown in Figure 4.5.

Figure 4.5 shows two water consumption peaks, one from 6:00am to 9:00am and one from 4:00pm to 9:00mp. The first is due to the occupants waking up and preparing for work, while the second is due to their return from work.

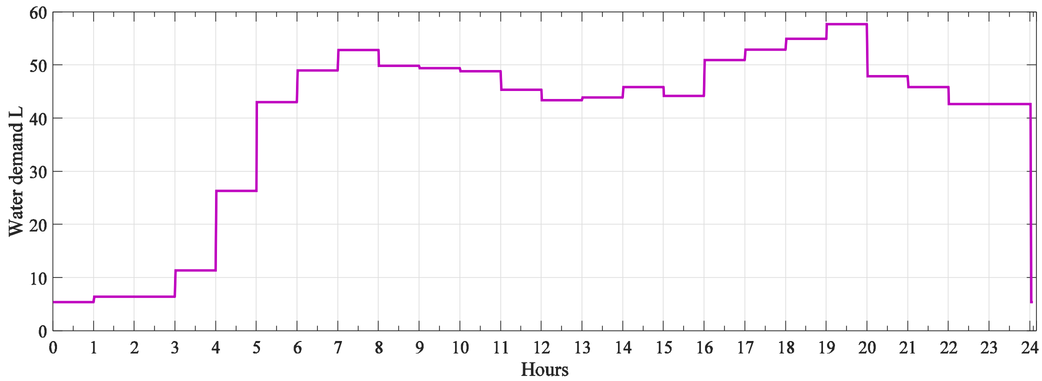


Figure 4.5: Estimated Hourly Water Demand Profile of a Single House in N. Cyprus (Panayiotou, et al., 2010)

4.6.2 Electricity Peak Demand Hours

Figure 4.6 shows the typical peak times for N. Cyprus, measured during January and June 2012 (KibteK, 2012; KibteK & TEIAS, 2015). The base demand is the average value of the demand (Ilkan et al., 2005), shown in Figure 4.6 as dashed lines, and is computed to be 221MW and 191MW, for summer and winter respectively.

The peak hours are those hours where the demand exceeds the base demand. The summer peak hours are approximately from 9:00am to 7:00pm, and the winter peak hours are from 5:00pm to 11:00pm. The longer period of 10 peak hours in the summer is selected to investigate the control algorithm performance.

The N. Cyprus electricity authority, KibteK, has put smart electric meters into operation from January 2016 (LGC, 2015). These allow the authority to send end-users a signal of real-time peak hours. Therefore, the algorithm can be updated to track the peak hours on a real-time basis.

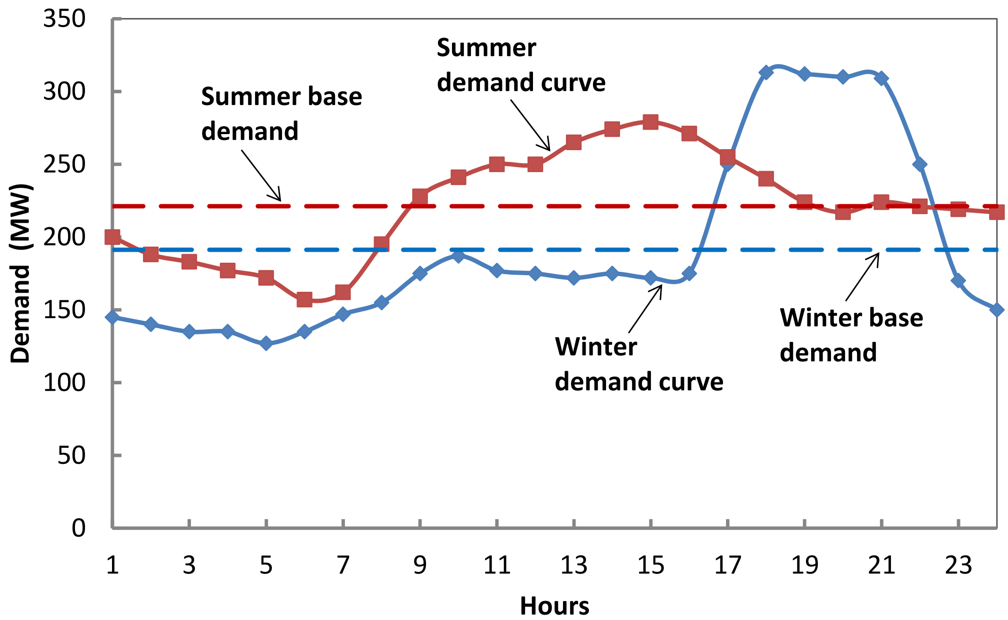


Figure 4.6: Hourly Electricity Demand Curves in N. Cyprus with Maximum Winter and Summer Peaks Obtained in 2012 (KibteK & TEIAS, 2015)

4.7 Results and Discussion

Based on the water demand profile shown in Figure 4.5, Figure 4.7 presents the simulation results for the existing water level controller. The pump starts 10 times during peak hours and 19 times over the whole day (Figure 4.7a).

The emptying and refilling cyclic volumes of the rooftop tank are preserved between $v_{ref} = 950$L and $v_{max} = 1{,}000$L (Figure 4.7c). The peak pumping energy and the ratio of pump operation R during a day are calculated using Eq. (4) and Eq. (5) to be 0.17kWh and 53% respectively.

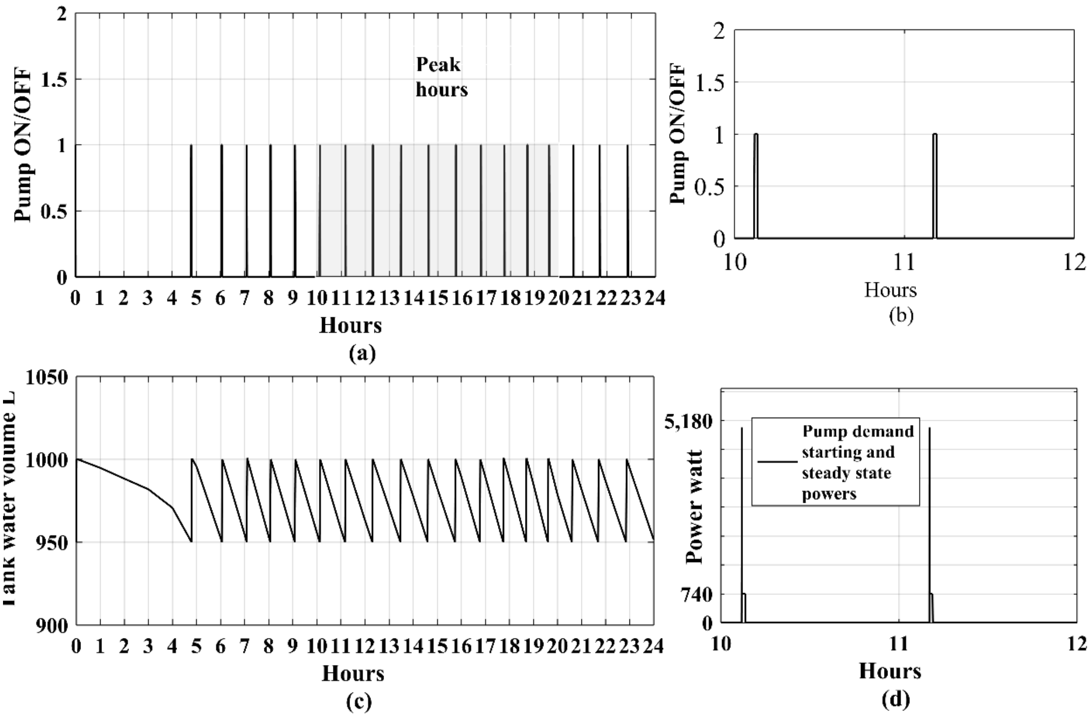


Figure 4.7: Simulation Results for the Currently Used Control Approach, (a) Operation Times of the Pump, (b) Selected on/off Cycle of the Pump, (c) Rooftop Storage Tank Volume and (d) Pump Start and Steady State Powers

These values are considered to be the base values for comparing the performances of the first and second control approaches. In the case of the first approach, v_{ref} is readjusted to 700L. The pumping times during a day are reduced to four times, two during peak hours (Figure 4.8a). The peak pumping energy is reduced to 0.128kWh, while the ratio R is reduced to 50%. The water volume boundaries are preserved between 700L and 1,000L (Figure 4.8b).

The first approach reduces both R and the pumping peak energy consumption at the expense of reducing the water supply pressure for the whole day. This approach is suitable whenever the shape and value of the water demand and peak hours do not change.

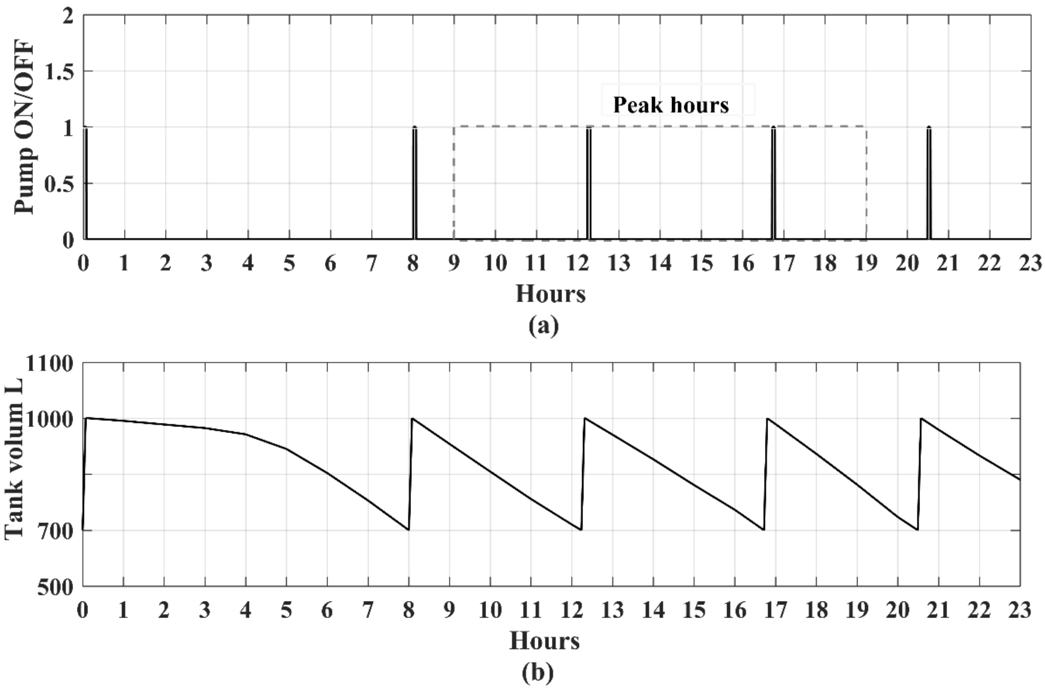


Figure 4.8: Simulation Results of the First Control Approach, (a) Operation Times of the Pump, (b) Rooftop Storage Tank Water Volume

The second approach depends on the water volume boundaries presented in Eq. (8) and Eq. (10). The control algorithm reduces the number of peak pumping times and shifts the pumping work to off-peak hours, compared to both the existing and first control approaches.

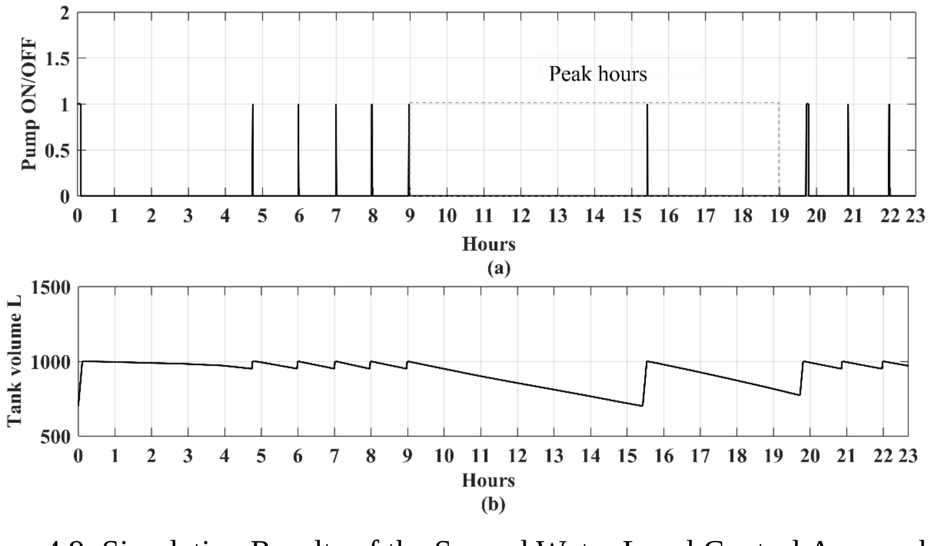


Figure 4.9: Simulation Results of the Second Water Level Control Approach, (a) Operation Times of the Pump, (b) Rooftop Storage Tank Water Volume

The total number of pumping times during the day is 11, one of which is during peak hours (Figure 4.9a). The ratio R is reduced to 9%, and the peak pumping reduced to 0.087kWh. The second control approach preserves the water supply pressure at a higher level for most of the day than the first control approach (Figure 4.9b).

Table 4.2 presents a summary of the pumping simulation results for the water level with the proposed control approaches for a single house during one day.

Table 4.2: Simulation Results of Water Level Control Approaches for One Day for a Single House

Controller type	Refilling volume L	Pump on at peak hours No.	Pump on during a day No.	Ratio of pump operation R %	Total energy for a single house at peak times kWh	Total energy for a single house at off-peak hours kWh
Current system	950	10	19	53	0.17	0.15
First approach	700	2	4	50	0.128	0.192
Second approach	950 off-peak 700 peak	1	11	9	0.087	0.233

4.8 Validation of the Water Level Control Algorithm

Open and closed loop model predictive control (MPC) strategies for controlling domestic water pump-storage systems in urban areas are introduced by Wanjiru et al. (2016). They use the water demand data shown in Figure 4.10. Their water storage system consists of a rooftop storage tank with a capacity of 1,000L and a 1hp water pump with a flow rate of 900L/h. Electricity peak hours are assumed to be between 7:00am and 10:00am and 6:00pm and 8:00pm.

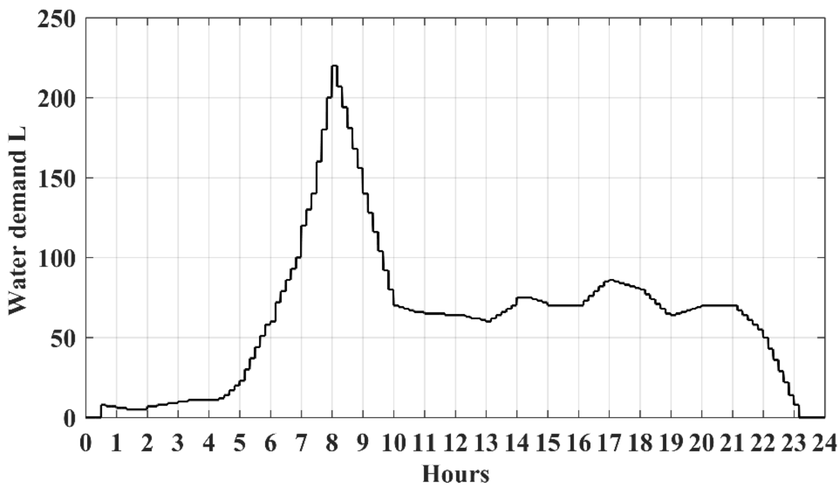


Figure 4.10: Validating the Water Demand Profile (Wanjiru et al., 2016)

The results shown in Figure 4.11, are obtained based on running the proposed control algorithm using the same data as Wanjiru et al. (2016) and the water volume boundaries given in Eq. (8) and Eq. (10) (the refilling volumes during peak and off-peak electricity demand hours of v_{ref} = 950L and v_{peak} = 700L). The pump turns on six times during the whole control horizon to satisfy the domestic water demand.

The operation of the pump at the beginning of the control horizon, lasts for 20 minutes (Figure 4.11a) to fill the tank from 200L to v_{max} of 1,000L, then it starts again at 8:00am to satisfy the peak water demand. Suitable indoor water supply pressure is assured by preserving the water volume in the tank at a volume between 1,000L and 700L (Figure 4.11b).

According to Wanjiru et al. (2016), the pump works 9 times with the open loop MPC and 5 times with the closed loop MPC, none of these times being during peak hours. However, the water volume in the tank is allowed to decline to 123L and 447L respectively, which decreases the indoor supply pressure. On the other hand, with the proposed algorithm, the pump operates once during peak time and ensures at least

700L of water is in the tank, keeping the end-use water supply pressure higher than that found by Wanjiru et al. (2016).

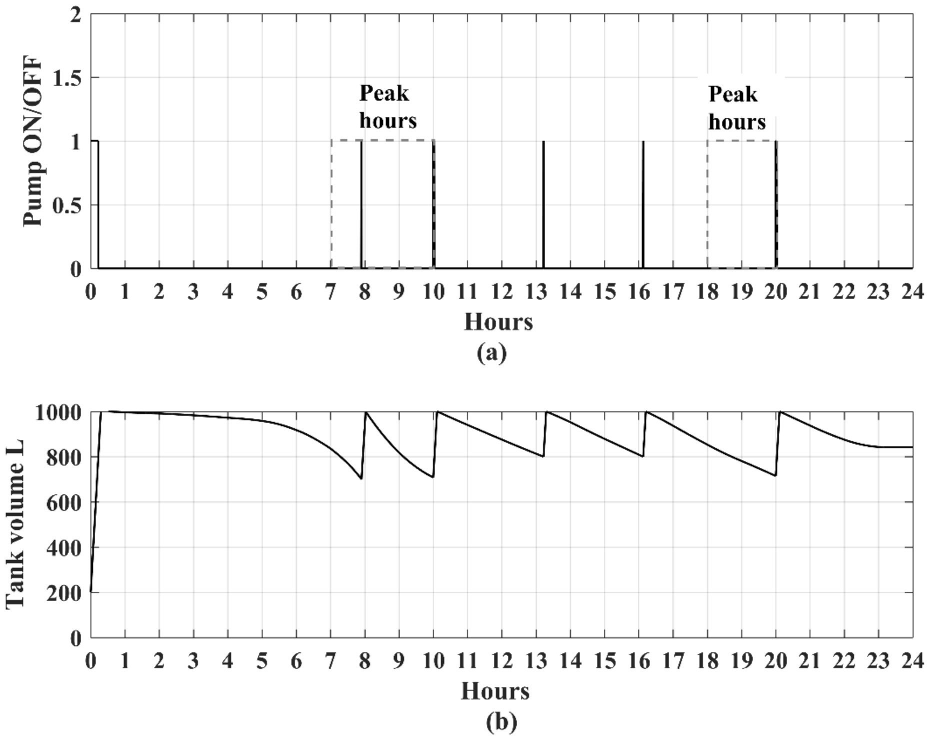


Figure 4.11: Algorithm Validation with Various Water Demand Profiles and Electricity Peak Hours (Vpeak = 700L)

It is possible to eliminate pump operation during peak hours if the water volume in the tank is allowed to drop to 400L during peak hours (Figure 4.12). With this new constraint the pump operates five times during the day, none being during peak hours. Moreover, the water volume declines to 400L only once during the first electricity consumption peak. The maintenance cost of the pump could be reduced by reducing the refilling volume during off-peak hours v_{ref} to a value lower than 950L, but this causes the indoor water supply pressure to drop to a value that can be felt by the end-users (especially in single story buildings or top floor apartments). In this scenario, water demand takes longer to satisfy and it may affect the operation of home appliances such as washing machines and dishwashers which require a certain water pressure to operate efficiently. Also, when the water in the rooftop tank drops below a certain level, air bubbles may occur in the supply piping system.

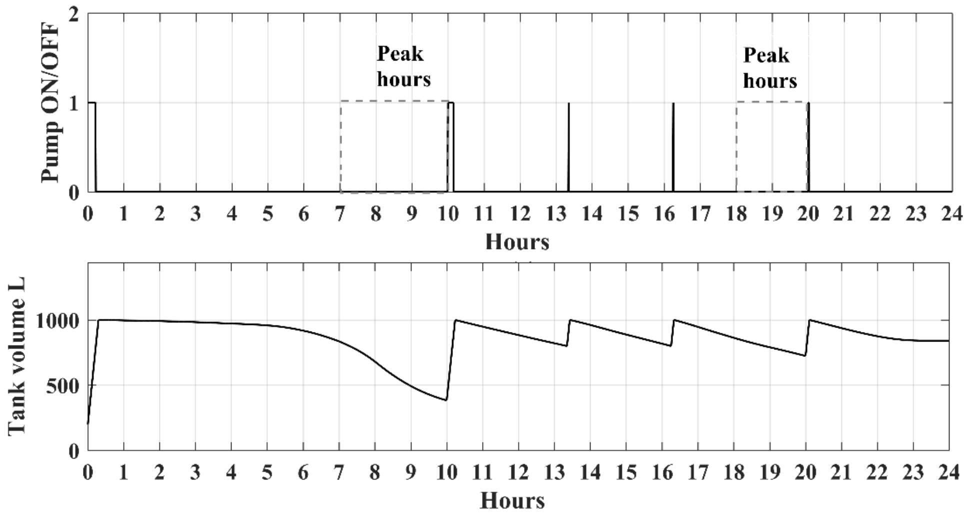


Figure 4.12: Algorithm Validation with Various Water Demand Profiles and Electricity Peak Hours (Vpeak = 400L)

4.9 Chapter Summary

The second control approach, using an algorithmic control strategy, requires a simple modification to the existing control scheme by adding an additional float switch in the rooftop tank. The algorithm tracks peak hours and the water level in the rooftop tank. During off-peak hours the algorithm cycles the pump between 950L and 1,000L, while during peak hours it cycles the pump between 700L and 1,000L. Due to this difference in cycling volume the pumping ratio is reduced significantly (R = 9%) keeping a satisfactory water supply pressure for most of the day. The algorithm is simple and requires low cost hardware with low computational capacity. Moreover it can be installed in both new and existing pump storage arrangements.

Chapter 5

ESTIMATING DOMESTIC POWER CONSUMPTION PROFILES

5.1 Introduction

In order to utilize the intelligent control approach in load management, daily power consumption profiles are needed. Unfortunately, such data is not available in most developing nations, particularly in Palestine where this study is conducted. Therefore, this chapter introduces a bottom-up model to estimate the domestic power consumption profiles. The model includes the consumers' behaviour of electricity use.

5.2 Place of Study: City of Hebron

The housing stock in Palestine consumes about 39% of the country total electrical power (PCBS, 2015). The utility (the electricity company) limits the share of each house either by 220AC Volt/25 Ampere or 380AC volt/ 32 Ampere automatic circuit breakers. For instance, if the house current consumption exceeds the limit the breaker automatically cut off the power . The utility also limits the current consumption of a group of houses, called a 'region' by an automatic circuit breaker; it's maximum current value depends on the size of that region. The limited share of electricity makes any householder thinks seriously before any decision to buy a new electrical device, especially, if the device operates on a high current only.

The city of Hebron has been selected for this study due to the long standing problem of power outages. It is located in the West Bank about 35 km south of Jerusalem. It is considered one of the largest cities in the West Bank in terms of land and population . The city area is about 42 Km^2 (PCBS, 2015) and the population number of the city reaches about 684000 in 2016.

5.3 Methodology

5.3.1 General Approach

The flow chart in Figure 5.1 presents the steps followed in developing the power consumption model. These steps are explained in details in the following sections.

5.3.2 Recording the Power in Selected Houses

Recording of the electric power consumption of ten houses in Hebron is conducted. The purpose of this data is to study the nature of the house's power consumption in Hebron, and to specify the peak of consumption hours. And also to determine which electric loads that have high power consumption. The consumed current and the voltage for each house are recorded for 24 hours every one-second measurement interval. The measurement tools are listed in Table 5.1.

The current and voltage transducers are connected to the main supply electric line of the house as shown in Figure 5.2. The data logger is programmed to record the measured data every one-second interval. The data recorded by the logger is evaluated using HOBO software.

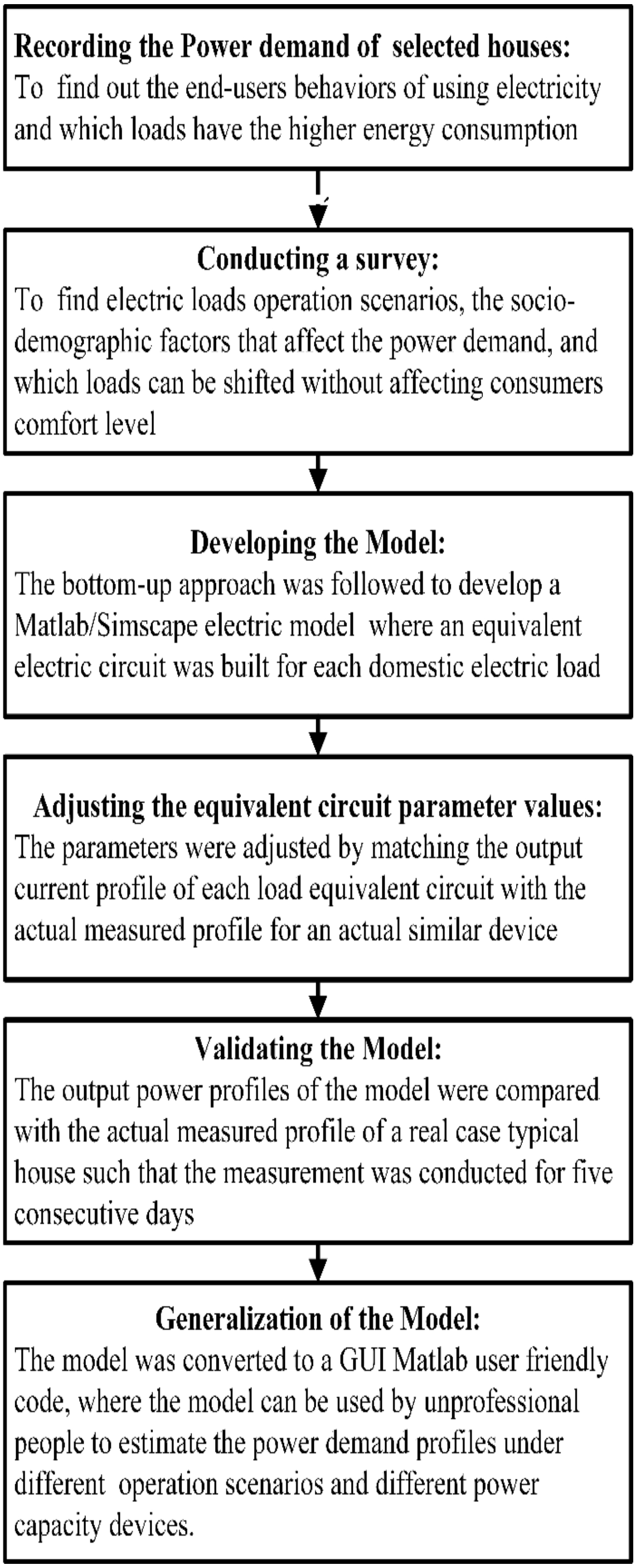


Figure 5.1: General Modelling Approach of Power Consumption

Table 5.1: Measurement Devices Specifications

Device	Measured quantity	Specification
Potential Voltage Current Transformers SPT-0375	Voltage	1. Voltage current transformer with 115 to 460-volt AC 2. Linear output voltage proportional to the input voltage, with a linear accuracy of ±1%
Split core AC current sensor	Current	1. The capacity of current measurement is from 0 to 20 Ampere 2. The sensor is compatible with HOBO U12data loggers 3. The sensor approximated response time is 440 [msec] 4. An accuracy of ±4.5% at full scale
HOBO U12 Data Logger	Data logger	1. A 12-bit resolution logger 2. Record up to 43,000 measurements. 3. A USB interface is used for launching the readout data to the computer

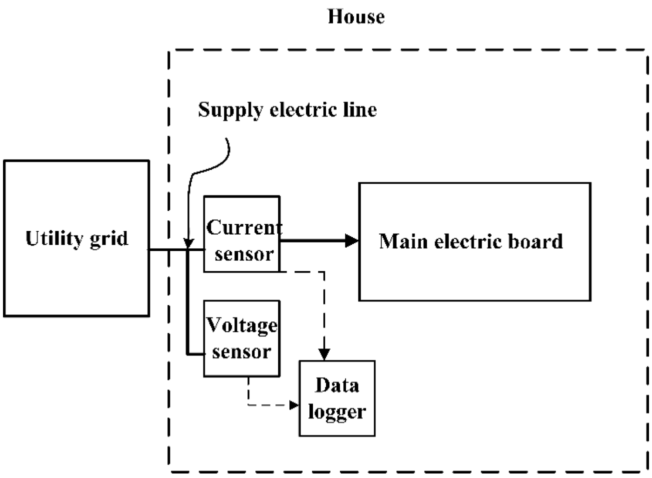


Figure 5.2: Measurement Devices Setup

5.3.3 Conducting the Survey

A survey is distributed accompanied with the measurements that were conducted. The purpose of the survey is to determine the operation scenarios and the nominal powers ratings of the electric loads in these houses. The main purpose is to estimate the effect of some of the socio-demographic factors—such as, number of family members, house surface area and family monthly income—on domestic power consumption. The survey is shown in (Appendix B).

Table 5.2: Summary of the Survey

House #	Number of family members	Number of members at school	Number of Members at university	Work of the Householder		Monthly Income (US$)	House surface area m^2	Day consumption kWh	Night consumption kWh
				Wife	Husband				
1	7	2	1	hk	Dealer	>1500	180	9.07	11.68
2	7	3	2	Employee		1000-1500	150	1.74	6.17
3	8	3	2	hk	Technician	1000-1500	180	5.22	11.2
4	6	3	1	hk	Dealer	1000-1500	170	4.42	5.42
5	8	1	1	hk	Dealer	1000-1500	170	3.34	4.66
6	9	4	1	hk	Dealer	1000-1500	120	3.25	0.5
7	7	3	1	hk	Technician	1000-1500	150	3.26	2.44
8	6	1	2	hk	Dealer	1500	150	6.83	8.1
9	7	2	1	hk	Government employee	>1500	180	13.98	14.3
10	6	3	1	hk	Technician	1000-1500	140	4.63	4.11

Table 5.2 lists the data summary of the survey. The table shows the recorded data of the socio-demographic factors which affect the domestic power demand. These factors are the family monthly income, house surface area, number of family members, the availability of family members at day or night time, and the number of family members either at school or at university (see Appendix B). The power consumption during night and day time are collected and calculated from the current and the voltage recorded data of each house.

5.3.4 Power Consumption Model

Domestic power demand varies from house to house based on two dominant factors. The first is the way and time period occupants operate their loads. The second factor is the number and power ratings of these loads. Therefore, to attend to these effects, an end-user basis operation scenario and an electric loads power rating have to be identified in each surveyed house.

Based on the above considerations and assumptions, Figure 5.3 represents the conceptual design of power consumption model of a typical single house of Palestinian house stock. The input power from the utility energy company is limited by an automatic 25 Ampere circuit breaker. The useful input power which supplies the electric loads is extracted after multiplying the utility grid input power by the indoor power factor ($P_g P_h$) such that, the utility grid power factor (P_g) can be assigned a value from 0.7 to 0.85 (Abualkhair, 2006), while the indoor (P_h) is to be calculated for the modelled house because it depends mainly on the type of house's electric loads.

An equivalent RLC electric circuit is constructed for each electric load. The equivalent circuit followed the design nature of the load. In other words, the loads can be divided into resistive, inductive and capacitive loads. The power rating capacity and the parameters of the electric elements of these equivalent circuits have to be installed in each particular house.

The output power profile consumed by the loads is calculated by the model based on the equivalent circuit for each load. The effect of all other factors such as socio-demographic on the total output power consumption profile was included in the model as an operation scenario data that has to be inserted for each particular end-user. The model is used to predict any end-user power consumption profile, also the model is expandable such that any new electric load can be added easily in the model.

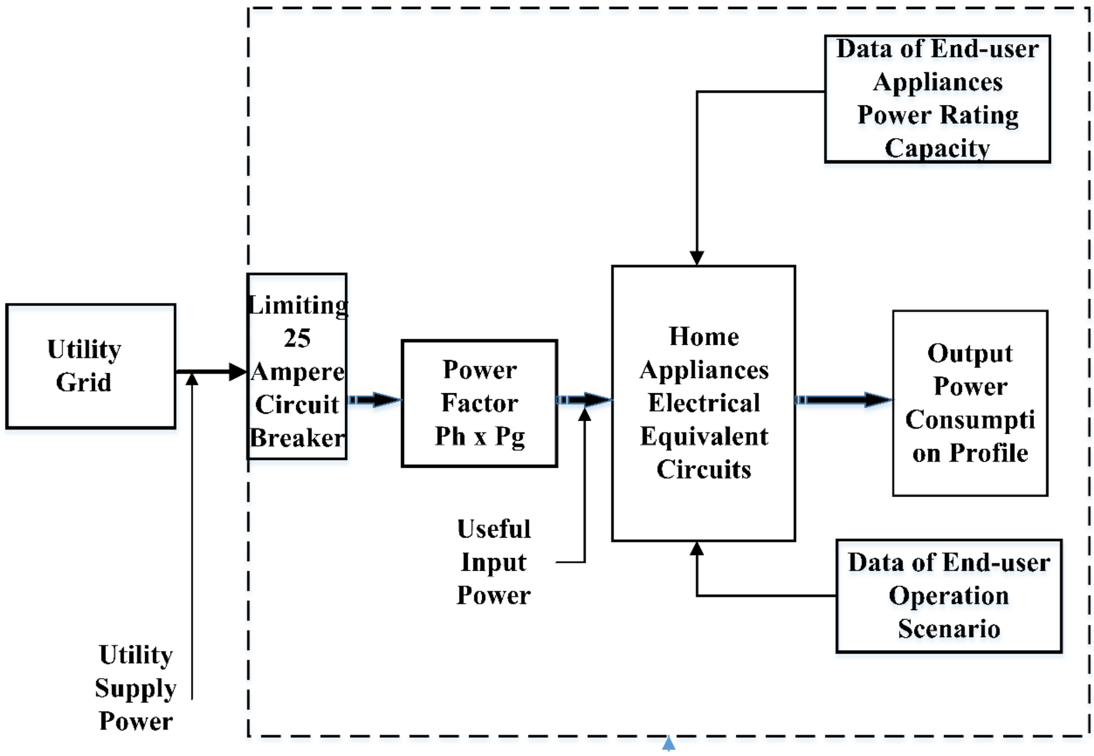


Figure 5.3: Conceptual Design of Typical Palestinian House Power Consumption Model

5.3.5 Matlab/Simscape Model

Simscape Matlab toolbox is used to construct the equivalent electrical circuits of the loads. To simulate the indoor electrical grid of the house, all the electric loads are connected in parallel to a single phase 220/50 Hz AC voltage source as seen in the model presented in Appendix D. Two graphs are generated from the model; the first graph represents the total RMS current during 24 hours, the second graph represents the total power consumption profile during 24 hours. The average output power is calculated by use of Eq. (11).

$$Power = P_T \, I_{rms} \, V_{rms} \tag{11}$$

Where $P_T = P_g \, P_h$ Total Power Factor

I_{rms}: RMS AC Current

V_{rms}: RMS AC Voltage

P_g was given a value of 0.8 while P_h is calculated by the model for the total loads in the house.

The error between the model output and the actual measured power is calculated based on Eq. (12):

$$error = \frac{Model\ output\ total\ energy\ - Actual\ measured\ total\ energy}{Actual\ total\ energy} 100\% \qquad (12)$$

5.4 Results and Analysis

5.4.1 Survey Analysis

Using the data in Table 5.2 and Matlab curve fitting tool Figure 5.4 and Figure 5.5 shows the results of the multi-linear regression conducted to examine the mathematical relationship between the house surface areas, family incomes, and the daily total electric energy consumptions. It can be concluded from the results listed in Table 5.3 that there is no significant regression relationship between electric energy consumption and the number of family members. This is observed from the low value of regression factor R and the high value of Root Mean Square Error (RMSE). On the contrary, there is a significant relationship between family income, house surface areas and power consumption, that is, as these values increase, power consumption increases too.

Table 5.3: Multi Linear Regression Results of Family income, Houses' area against Daily Electric Energy Consumption

Data	Fit type	R-square	RMSE
House surface area against daily house electric energy consumption Figure 3.1 (Figure 5.4a)	Cubic polynomial	0.6883	5.2153
House family income and daily house electric energy consumption (Figure 5.4b)	Cubic polynomial	0.9577	1.5691
Number of family members at day time against day consumption	Smooth spline interpolation	0.3621	3.2971
Number of family members at night time against day consumption	Smooth spline interpolation	0.3158	4.1513

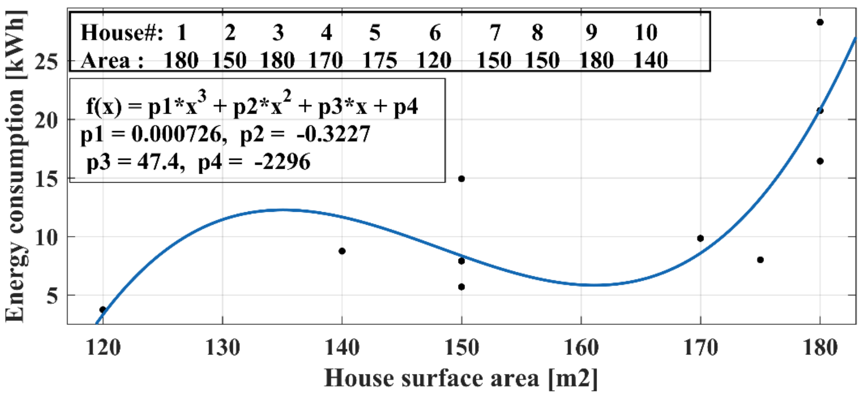
Figure 5.4 demonstrates the following findings:

1- The dominant factors affect the family electric energy consumption are the income and the house surface area. For example, house 1 and house 9 have the highest electric energy consumption. this is due to their high monthly incomes, more than 1500 US$, and houses' surface areas; approximately 180 m^2.

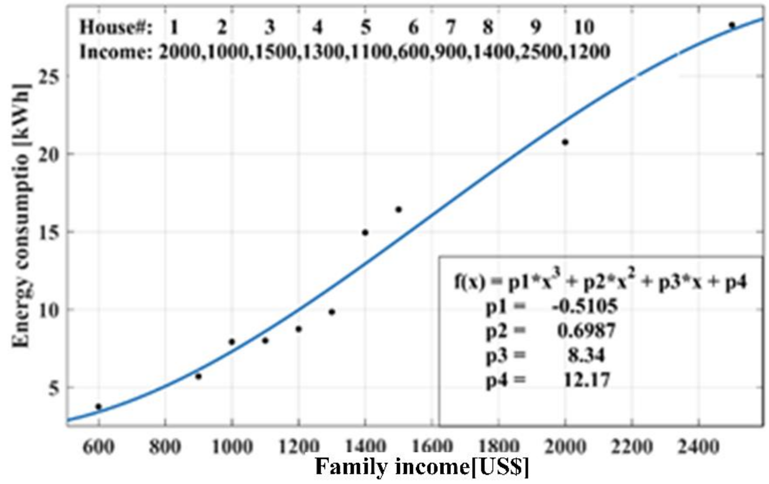
2- As the house surface area increases the electric energy consumption increases. Figure 5.4a shows this clearly for houses with surface areas greater than 150 m^2.

3- Despite the similarity between the surface areas of some houses, the electric energy consumption still varies if the income is different. With the same measure, if the income is approximately similar the consumption will be relatively the same; this is clearly indicated in Figure 5.4 in the case of houses 4 and 5.

4- The number of members has no significant effect on electric energy consumption if the income is low or the surface area is not high. In the case of house 6, the family has the highest family member's number of 9 members while their house area is 120 m^2 and their income is 1200 US$.

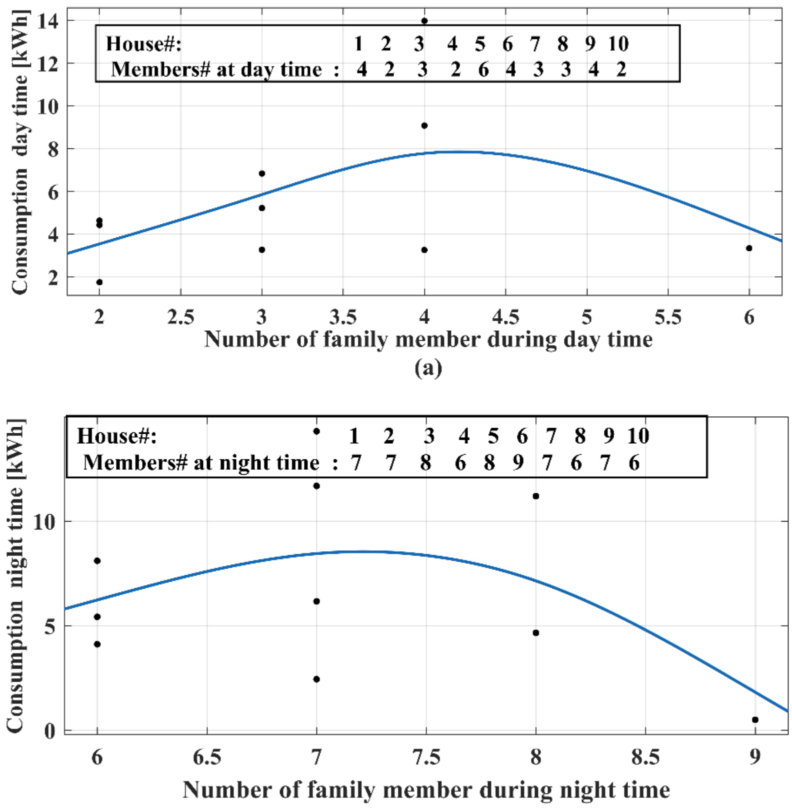


(a)



(b)

Figure 5.4: Socio-Demographic Factors Affecting Power Consumption, (a) House Surface Area against Daily House Electric Energy Consumption, (b) House Family Income against Daily House Energy Consumption



(b)

Figure 5.5: Availability of Occupants' Effect on Power Consumption, (a) Number of Family Members at Day Time against Day Consumption, (b) Number of Family Members at Night Time against Day Consumption

Based on the analysis of the data in Figure 5.5 the following results can be estimated:

1. The (the daily?) electric energy consumption of some houses mostly the same as exemplified in the case of houses 4, 5, 7, and 10. The consumption is due to the high number of family members at home during day time, such as the case of house 5 where 6 members are noted to be at home during day time. Electric Energy Consumption is also related to the high number of family members who attend school or university as shown in the case of houses 4, 7 and 10, where those students had wake up early in the morning and prepare themselves to start school or university at 8 o'clock morning.
2. The night electric energy consumption increases with the increase in family members that are university students. In the case of houses 2, 3 and 8 the university student's number is s 2 compared to the rest of the houses where one family member is at university. Evidently, the night consumption increases in this situation as the university students need electricity for computers and lightening to carry out their university course works, assignments and readings.

5.4.2 Power Measurement Analysis

Power demand profiles for 10 houses in City of Hebron are recorded. As an example, the analysis of power demand profiles of house 1, 2 and 3 are presented below.

House 1:

Figure 5.6 and Figure 5.7 show power profile consumption of house 1 for 24 hours. As it is shown in Figure 5.6, the period from 7:20 PM to 10:18 PM is the highest consumption during night time. In this period, the active home appliances are: the TV, the water heater, the air condition and the lighting system.

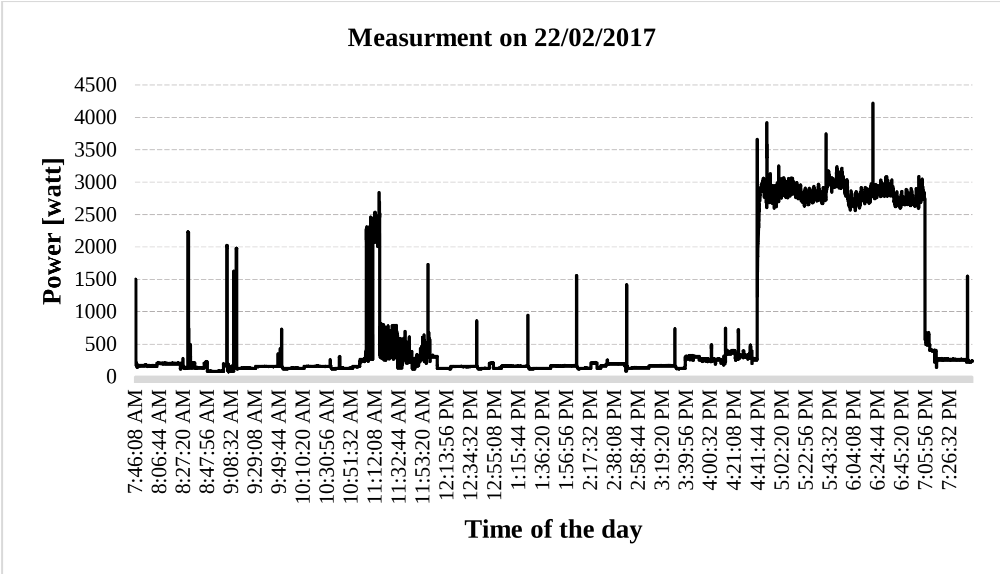


Figure 5.6: Power Consumption from 7:00am to 7:00pm of House 1

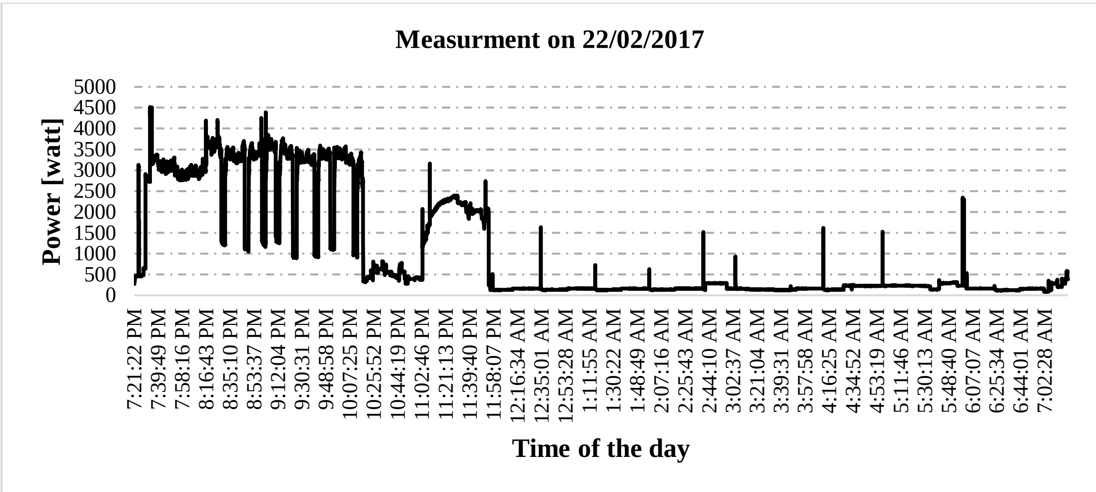


Figure 5.7: Power Consumption from7:00pm to 7:00am of House 1

Figure 5.7 shows that the electric heater is in use for about 46 minutes between 11:05 PM to 11:51 PM. The highest consumption is from 4:41 PM to 7:04 PM. Figure 5.6 shows that the washing machine and the air condition are in use. The total electric energy consumption of house 1 is high and hit record of 20.75 kWh; this can be related to the high monthly income and the high surface area of the house. The high monthly income encourages the householder to buy additional loads such as air conditioners.

Besides, it is noticed that the size of the lighting system is higher compared to the other houses in the sample.

House 2:

Figure 5.8 and Figure 5.9 show power profile consumption of house 2 for 24 hours. As shown in Figure 5.8, points 1, 2 and point 3 represent the period of supper time. The devices operating at that time are: the water heater, the microwave and the boiler, respectively. The boiler is in use again at point 4; which is the dawn time. Point 5, which is between 5:30 AM to 7:15 AM, when the family waked up in the morning and put on the washing machine, the boiler and the hair dryer.

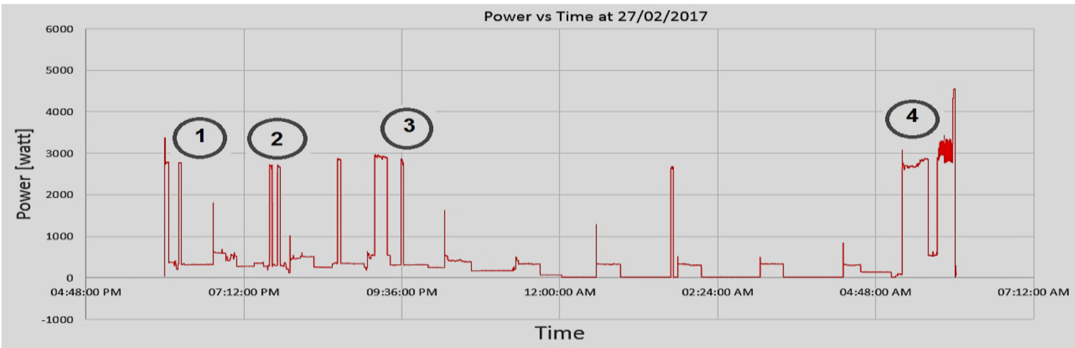


Figure 5.8: Power Consumption from 6:00pm to 6:00am of House 2

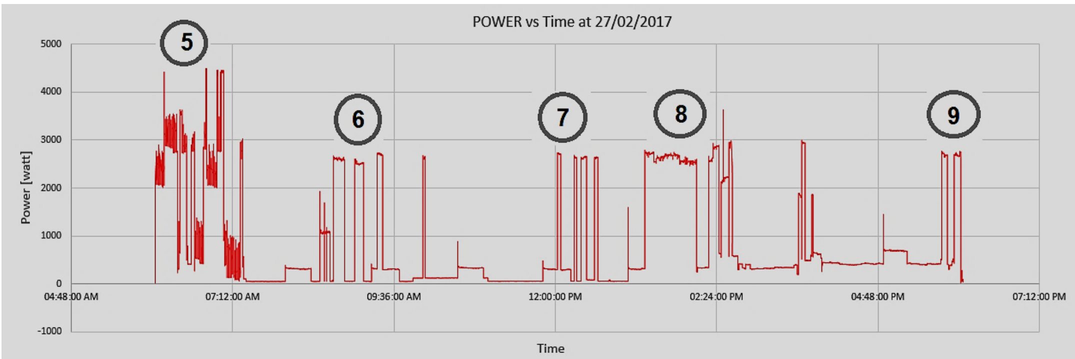


Figure 5.9: Power Consumption from 6:00 AM to 6:00 PM of House 2

At point 6 and point 9 the vacuum cleaner is working, while at point 7 and point 8 the microwave and the electric fireplace are working respectively to prepare the lunch food and to heat the place when students returns from the school. According to the information obtained from the questionnaire of the house 2, it is found that consumption of electricity is distributed during most of the day because of the presence of the family members in the house, and the wife (or husband ???) has to carry out the home duties, such as, laundry, cleaning, cooking and etc. The total consumption of house 2 was 7.91 kWh whereas, the monthly income of the house is normal.

House 3:

Figure 5.10 and Figure 5.11 show power demand profile of house 3 for 24 hours. Figure 5.10 indicates the increase in power demand is due to the water heater and the water pump at points 1 and 2 are being in use, while at point 3 and point 4 the electric fireplace is in using.

As shown from Figure 5.11 point 5 and point 6 represent the operating devices, which are: the water heater and the washing machine, respectively. While at point 7 the electric fireplace and the water heater are working at the same time. According to the information obtained from the questionnaire for house 3, the electricity consumption was high during most of the day; noticeably, the measurement is recorded during the weekend. Moreover, the total electric energy consumption of the house was high; equal to 16.42 kWh during the day. Although the monthly family income is moderate the consumption was high, and this is evidently attributed to the high surface area of the house, which is 180 m^2.

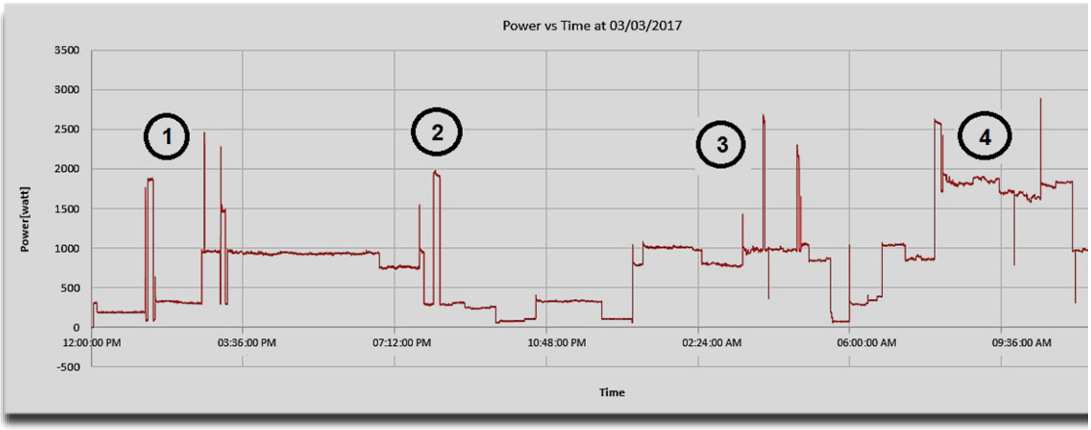


Figure 5.10: Power Consumption from 12:00 PM to 10:00 AM of House 3

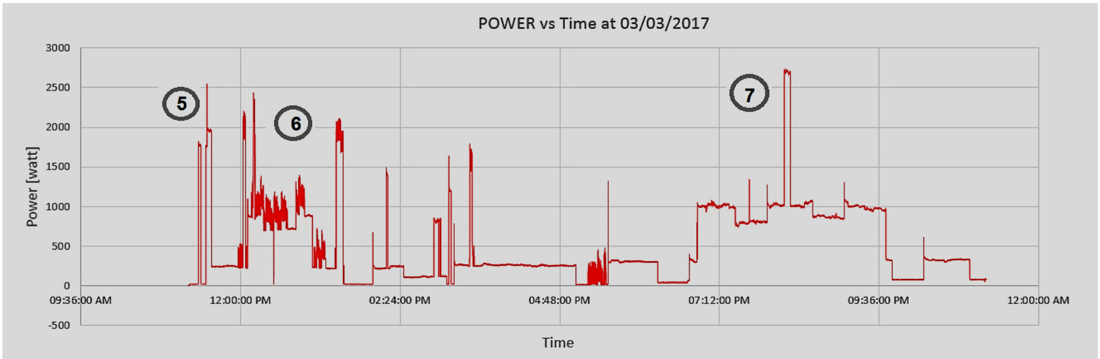


Figure 5.11: Power demand from 10:00 AM to 12:00 PM of House 3

Based on the above analysis, the variables which mostly affect the domestic power demand and are the concern of this research can be clustered as follows:

- Electrical utility distribution grid power factor (P_g) reaches a low value in Palestine of 0.7, consequently, the low value of power factor increases the electric energy consumption (Abualkhair, A., 2006). Moreover , the low value of the indoor house power factor (P_h) depends on the age and of the indoor electrical network, therefore, the type of the electrical loads increases the electric energy consumption (Ibrik & Mahmoud, 2002). Power factor (P_g) could be given a value from 0.7 to 0.85 (Abualkhair, A., 2006), while (P_h) is calculated for individual houses.

- . Day consumption increases with the increase of family members at home, and with the job type of the wife. A drastic increase in daily consumption between 5:30 AM to 8:00AM in the morning in particular for families which have students attending schools such that, they had to get themselves ready in the morning. Another indicator of drastic increase, is between 4:00PM and 6:00 PM when the family members are back home.
- Night consumption increases with the increase of the number of the family members that are university students. The increase is due to the use of the lighting system and other devices, such as computers or tablets for long hours for studying purposes (or entertaining purposes, such as gaming ??). The peak consumption is observed to be between 6:00PM and 11:00 PM during night time. In some houses a peak consumption is between 3:00AM to 4:30AM; this is due to some of the family members wake up for praying.

5.4.3 House Electrical Loads

Table 5.3 shows a summary of the common electrical loads in the houses where the measurements are taken. Loads could be classified into: high energy consuming devices with the ability to shift and operate during “off-peak” hours under special constraints. And high energy consuming devices that cannot shift as it disturbs the end-users comfort life level; either low or moderate energy consumers due to the short period of operation. The information in Table 5.4 is the basis for the shifting controller that are designed in this research.

Table 5.4: Classification of the Common Houses' Electrical Loads Based on Energy Consumption Level and Ability to Shift to "off-Peak Time"

Device	Power(watt)	Electric energy consumption	Shifting ability	Constraints of shifting
Washing Machine	700-3000	High	yes	If the load is in operation either during peak or off peak hours, it cannot be interrupted
Hair Dryer	700-1000	Moderate	No	
Microwave	1250	Low	No	
Toaster	1000	Low	No	
Clothes Dryer	2000	High	Yes	If the load is in operation either during peak or off peak hours, it cannot be interrupted
Electric furnace	1500	High	No	
Water pump	560-2240	High	Yes	High energy consumer due to frequent operation. It can be stopped or started freely if the water level in the storage tanks is monitored.
Water electric Boiler	2500	High	Yes	Using insulation material in the construct design of the boiler enables it to shift and operate during "off peak hours"; as a result, the warm water is ready when needed. The periods the warm water is needed are observed in the mornings and the evening times.
Air conditioner	2500	High	Yes	Due to its meticulous construct design, it controls temperature efficiently. However, the required cooling temperature can be adjusted at lower value during off peak compared to peak hours. Thus, less operation energy is required during peak hours.
Vacuum Cleaner	1400	Moderate	No	
Electric Fireplace	1000-3000	High	No	
Dishwasher	2200	High	Yes	If the load is in operation either during peak or off peak hours, it cannot be interrupted.
Refrigerator	500-1000	High	Yes	According to its nature of construction, it is a temperature controlled. However, the required cooling temperature can be adjusted at lower value during off peak than that during peak hours. Thus, less operation energy is required during peak hours.
Lighting System	500-1000	High	Yes	The house could be equipped with a storing lighting system, such that during off peak hours the system stores electric energy which can be reused during peak hours.

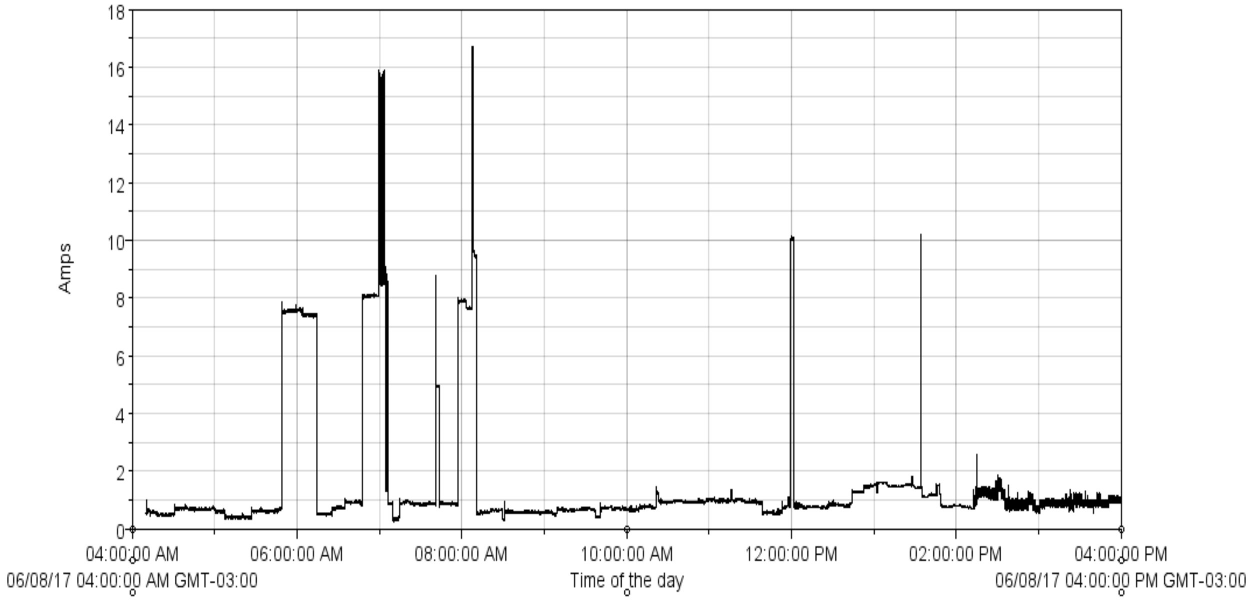
5.4.4 Validation of the Model

A house in Wadi Abu Dajan, located in the northwest of Hebron city was selected as the typical house to validate the model. The surface area of the house is 130 m^2. The family income is 1000-1500 US$. The house family consists of 4 members. The monthly power consumption of the house is proximately an average consumption. The actual current consumption profile for the house is monitored for five days, from 8/6/2017 to 12/6/2017 for 24 hours each one-second interval. The period includes the weekend days Friday and Saturday. Each of the measured profiles is compared to the model output current profile generated according to the operation scenario monitored in the house on that day.

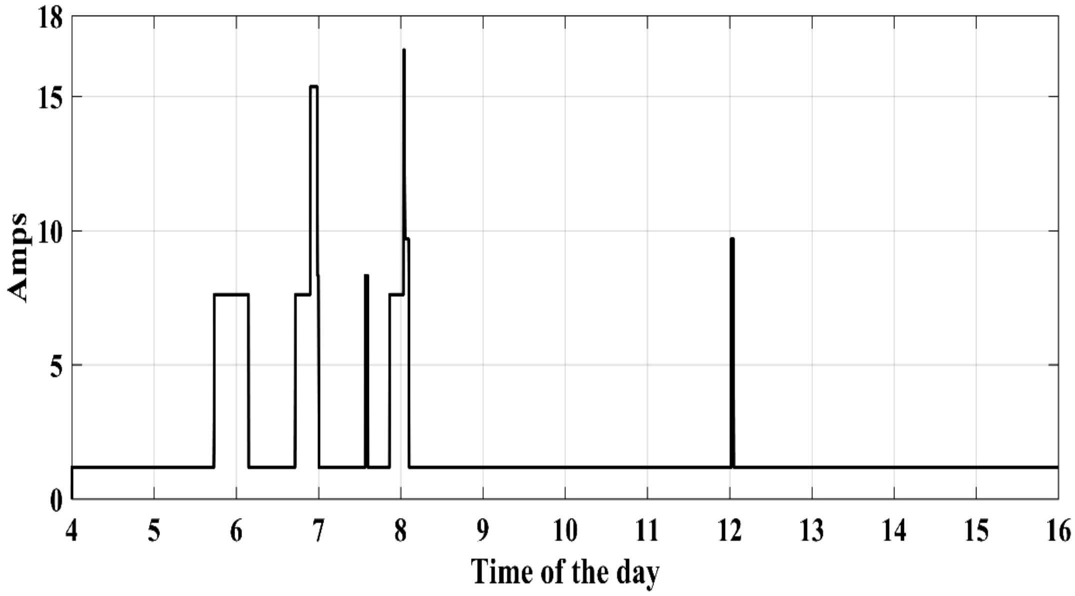
The figures shown in Appendix C describe the house electrical loads and their nominated power rating. But in order to adjust the parameters (R, L and C values) the actual current of each electrical load is measured. Such that, the generated output current from each electric equivalent circuit is matched to the actual measured current profile of that load. Loads listed in Appendix C are the basic loads which are found in any Palestinian typical house. Loads like HVAC systems or dishwashers usually are owned by high monthly income Palestinian families.

The generated current from the constructed model was compared to the measured current during the five days. Each day was divided into twelve hours a day and twelve hours night times. The measured current is recorded using HOBO software which is compatible software with HOBO measurement data loggers. The model in each time period runs under the conditions of the operation scenario of the houses' electrical loads recorded for the house in that period. The results of the two days are recorded and compared in the following section.

Load's Operation Scenario on Thursday 6/08/2017 during the day and night times is as follows: The water boiler operates from 5:40 AM to 6:20 AM, from 6:43 AM to 7:15 AM and from 7:52 AM to 8:10P AM. The electric oven operates for about 15 minutes around 12:00 AM; for the rest of the measurement time. i.e, the lighting system and the refrigerator (see Figure 5.12). The water pump operates from 18:50 to 20:30 and from 20:50 to 21:00, the hair dryer, for about 10 minutes around 5:30 AM, for the rest of time, the TV, lighting system and refrigerator are in operation (see Figure 5.13).

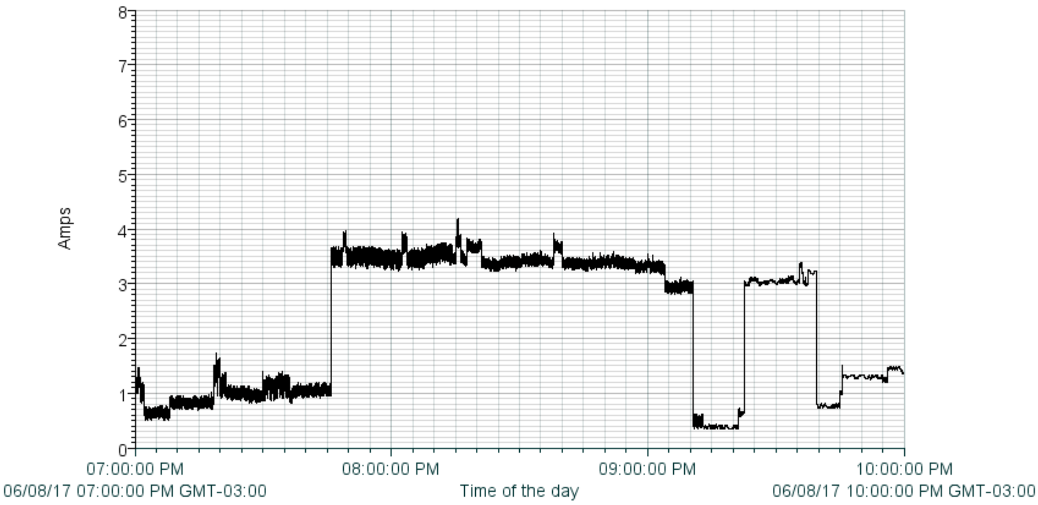


(a)

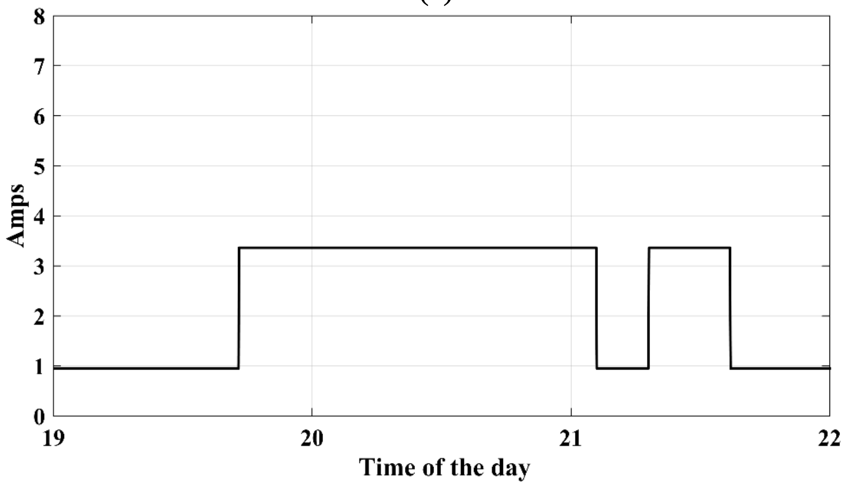


(b)

Figure 5.12: Current Profile on Thursday 6/08/2017 Day Time
(a) Actual Measurement (b) Model Output



(a)

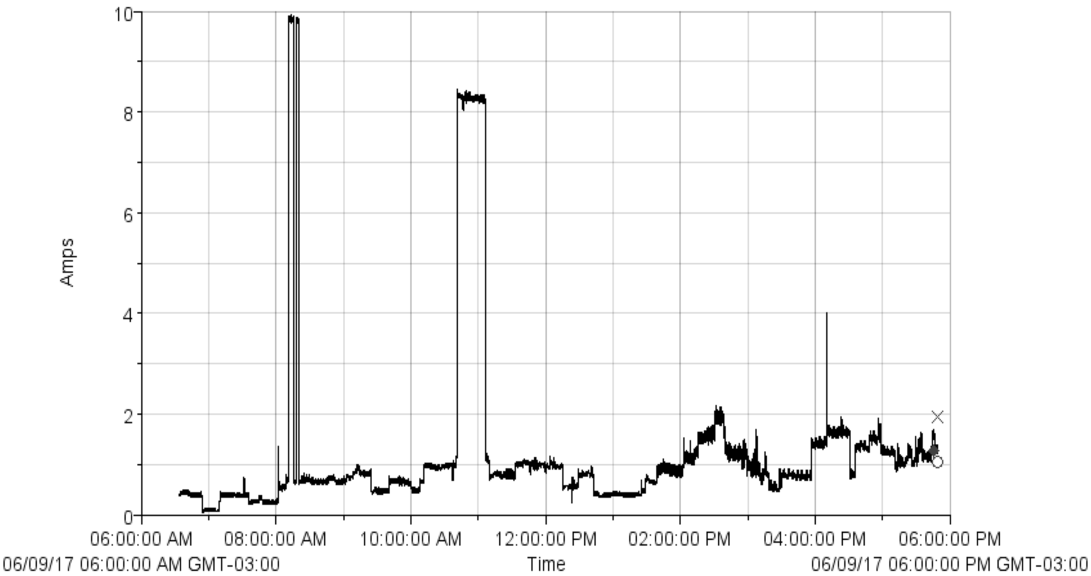


(b)

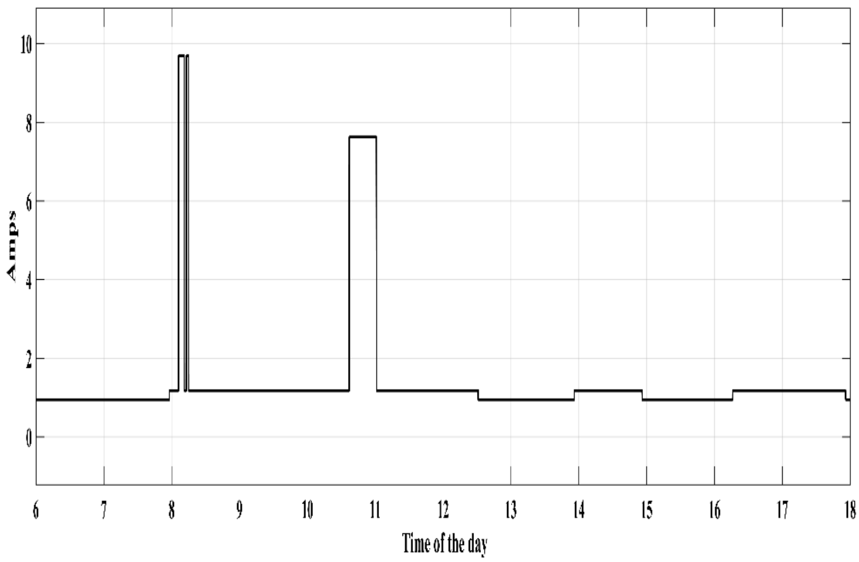
Figure 5.13: Current Profile on Thursday 6/08/2017 Night Time (a) Actual Measurement (b) Model Output

The total error between the electric energy consumption generated from the model and the measured electric energy consumption for that day was 15.2%. This error was due to the starting currents, especially, of the inductive loads as shown in Figure 5.12a and Figure 5.13a, such that the measured current is not smooth compared to the model output current. Another reason for the error is the inaccuracy in specifying and recording the exact operation periods of home appliances. These reasons of the error are generalized for the following days.

Figure5.14 and Figure 5.15 show the results on Friday 6/09/2017. The high power demand during day time was for 10 minutes between 8:15 AM to 8:25 AM such that the electric oven was in operation, and another period from 10:40 AM to 11:10 AM when the water electric boiler is in operation. During night time, the consumption was due to the operation mainly of the refrigerator and the lighting system.

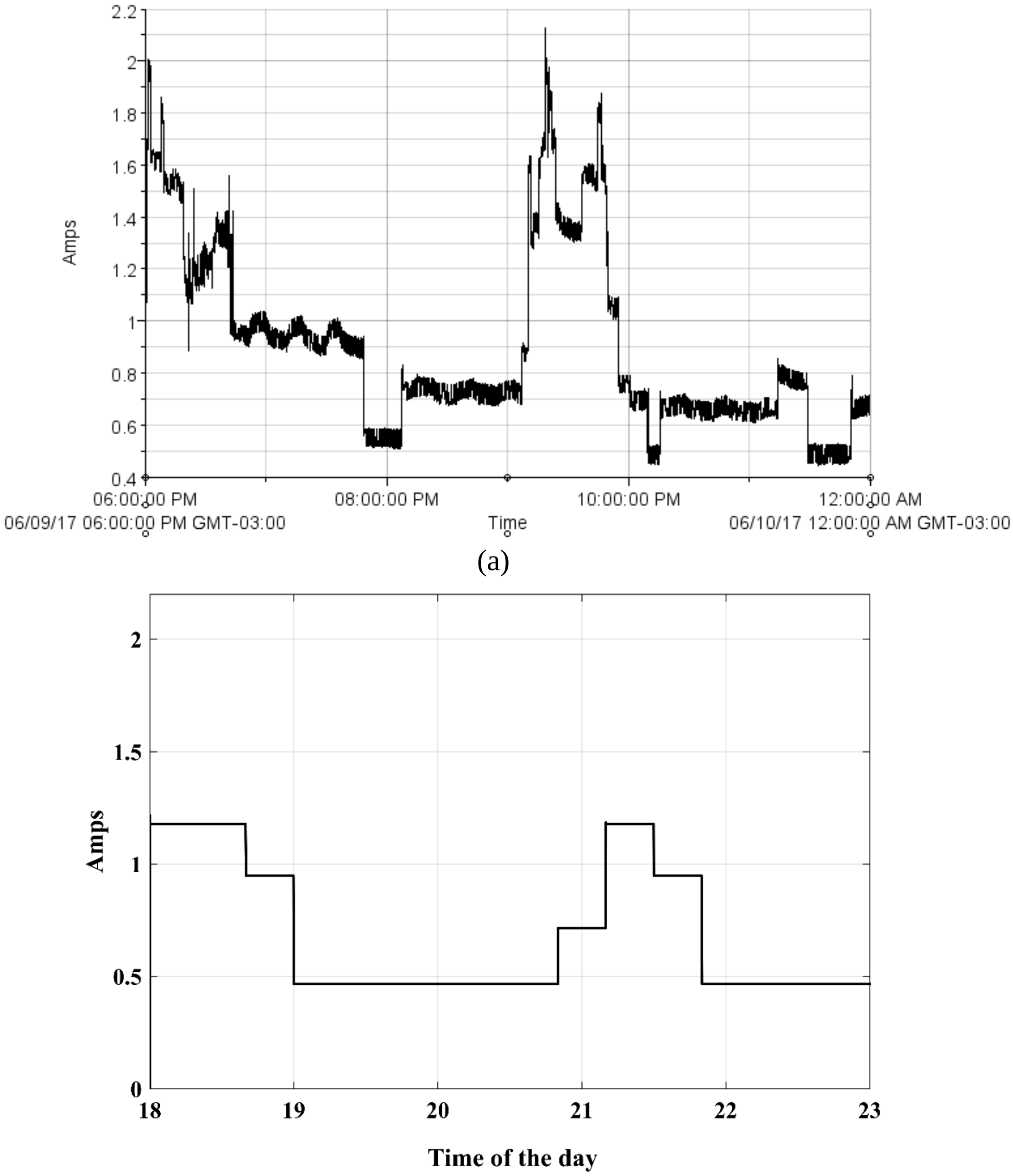


(a)



(b)

Figure 5.14: Current Profile on Friday 6/09/2017 Day Time (a) Actual Measurement (b) Model Output



(b)

Figure 5.15: Current Profile on Friday 6/09/2017 Night Time (a) Actual Measurement (b) Model Output

The calculated error percentage on Friday between the total generated by the model and the measured energy is at 7.8%. Table 5.5 lists all the calculated errors in the given days.

The average total error between the total daily electric energy consumption generated from the model and actual measured is at 8%, this error is mainly due to the starting current of the electrical loads and to the inaccuracy of recording the operation periods of these loads.

Table 5.5: Comparison between the Model Electric Energy and the Actual Measured Electric Energy Consumptions for Five Consecutive Days of a Single House

Day	Model day energy consumption [kWh]	Model night energy consumption [kWh]	Actual day energy consumption [kWh]	Actual night energy consumption [kWh]	Total error 100%
Thursday	3.75	3.46	3.15	3.10	15.20
Friday	3.65	1.47	3.00	1.75	7.80
Saturday	2.18	1.56	2.10	1.54	2.70
Sunday	2.85	1.80	2.58	1.85	5.00
Monday	2.18	1.45	2.00	2.10	-11.50

+ error means model power > actual power, - error means model power < actual power.

5.5 Generalization of the Model

The developed electric energy mathematical model is converted to a Graphical User Interface (GUI-Matlab) program. The purpose of the GUI program is to generalize the mathematical model to estimate the current consumption profile for any end-user. As stated above the current consumption profiles are end-users based and depend on the electrical loads, power ratings and the operation scenarios of thee loads.

A demonstration example of using the GUI program is shown in Figure 5.16 and Figure 5.17. These figures present the current consumption profile of the same loads' power rating but with two various operation scenarios.

The simplicity of using the GUI program has many advantages: the program can be used in sizing the residential renewable energy systems depending on the instantaneous actual power demand of the end-users. The program could be used by energy authorities for the strategic planning regarding the future power demand. The program could also be useful for researchers in the DSM field who are always in need to recognise the power pattern profile as a first and basic step in designing and implementing DSM programs.

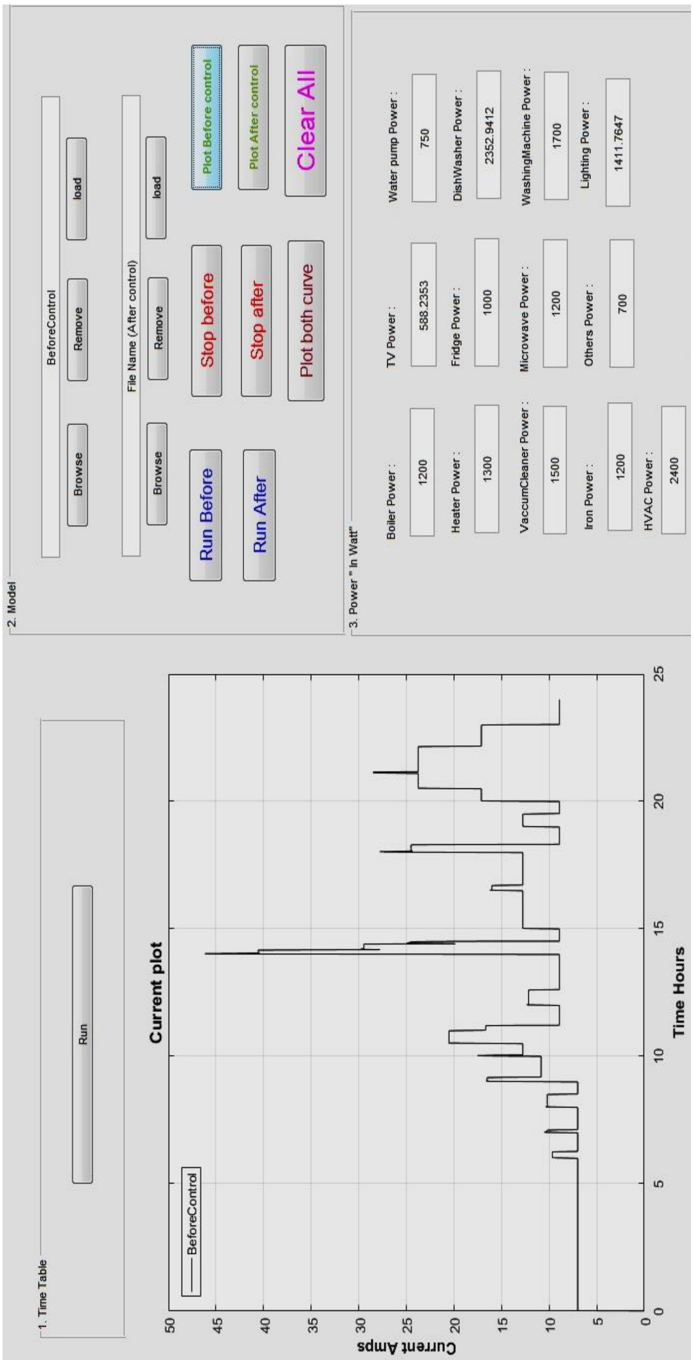


Figure 5.16: Current Profile Based on Loads Operation Scenario Example1

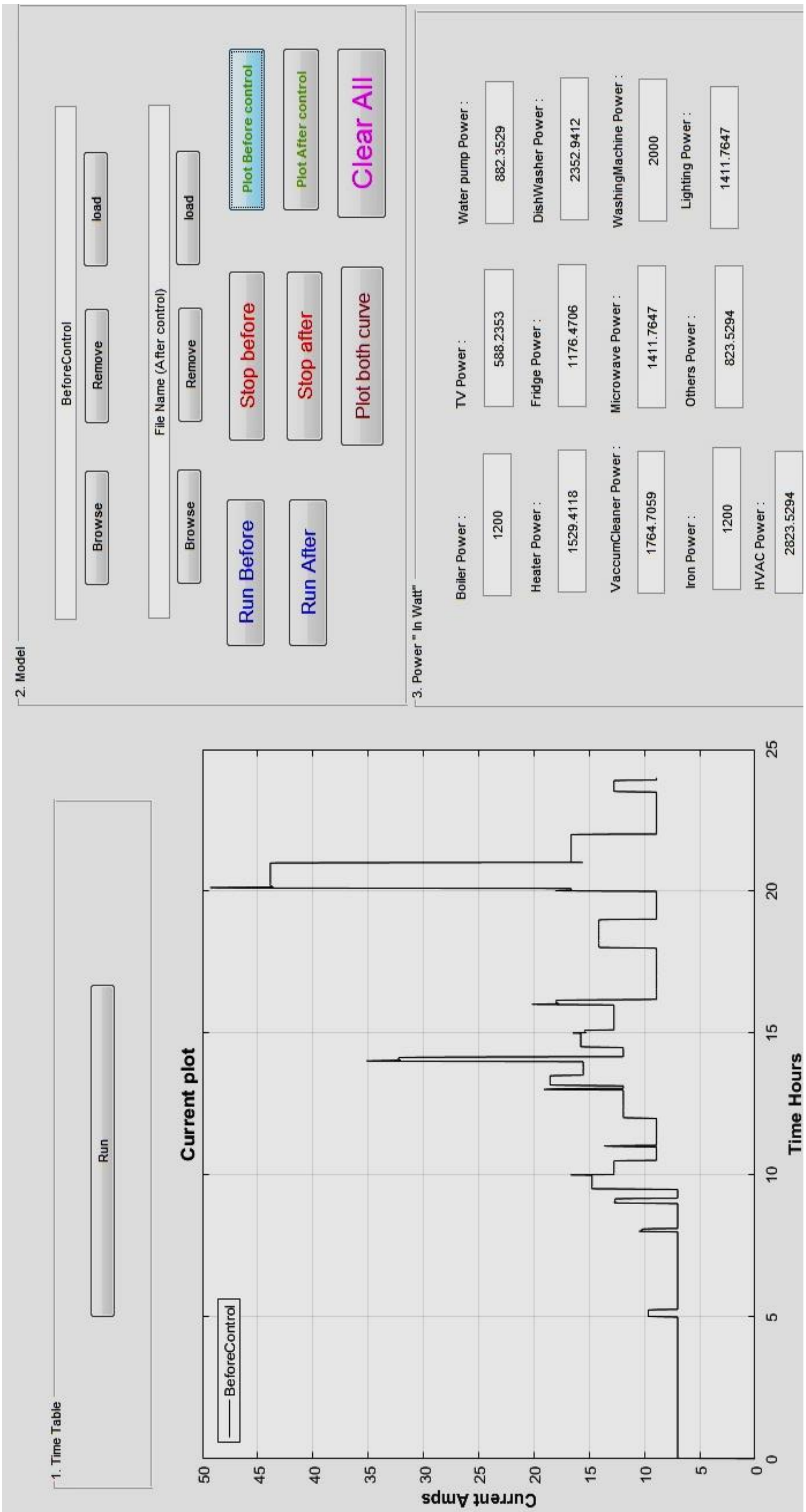


Figure 5.17: Current Profile Based on Appliances Operation Scenario Example2

5.6 Chapter Summary

Power Consumption Model has been designed for Palestine. The chapter investigated factors affecting power consumption. Inclusive are the socio-demographic factors, such as, family's income, house's surface area and the number of family members. Having applied power consumption bottom-up model, it attempted to make available for every end-user an estimate of their electrical power consumption, for which a graphical user interface is built. A detailed case study is conducted where power consumption is observed through five consecutive days is done, to further verify the suggested model.

Chapter 6

DOMESTIC ELECTRICAL LOADS FUZZY LOGIC CONTROL STRATEGY

6.1 Introduction

Depending on the analysis of the measured power profiles, the power consumption model developed and the analysis of the questionnaire data in chapter 5, it is worth to begin the following precise observations :

- Domestic power profiles are affected mainly by the power rating of electrical loads, the houses' surface areas and the income of the families. The profiles varies from house to house and may change instantaneously.
- Peak demand is not fixed to specific hours, it occurs at any time throughout the day.

This chapter introduces an intelligent closed-loop control strategy which continuously measures the house's total consumed current at real-time base. This measurement enables the controller to track the peak demand at any time, and compensate for any disturbance that may interfere or change the instantaneous power demand.

The residential sector in Palestine is considered for implementing the proposed strategy. The fuzzy logic control approach is used to avoid the problems of classical control methods. The problems include, the lack of an accurate mathematical domestic power demand definition, uncertainty in system parameters, and delay in real-time measurements. Fuzzy logic control is considered robust enough to deal with the prescribed classical control limitations (Jantzen, 2007).

6.2 Control Management Strategy

Figure 6.1 presents the conceptual block diagram of the proposed control strategy, which includes a model of each house, contained within a region. There is a fuzzy logic controller in each individual house within the region(in-house controller) and a fuzzy logic controller for the whole region (region fuzzy controller). The power consumption model presented by Ahmad and Atikol (2018) includes 14 domestic electrical loads, but the model shown in Figure 6.1 considers only six of the loads, the washing machine (WM), the dishwasher (DW), the electric water boiler (EWB), the electric water pump (EWP), the refrigerator, and the lighting system. The loads could be controlled without disturbing the end-users' comfort. The he in-house controller helps to redistribute the operation of the six loads to avoid house peak consumption. While the region fuzzy controller is the coordinates between houses and prevents the electrical appliances within the region to shift at the same time; and the regional current overload . The electricity consumption of each house in the region is limited by an automatic electric circuit breaker. In addition, the consumption of each region is limited by the region main automatic circuit breaker installed by the utility. The joint work of the fuzzy in-house controllers and the region controller contributes in solving the blackout problem. The KNX technology is used for data exchange between the in-house fuzzy controller and the controlled loads in the house. A communication protocol such as TCP/IP could be used to exchange data between the region controller and the in-house controllers. To implement this strategy, the region main distribution lines voltage rate is assumed to be 400 Vac and the houses voltage rate is assumed equal to 220 Vac.

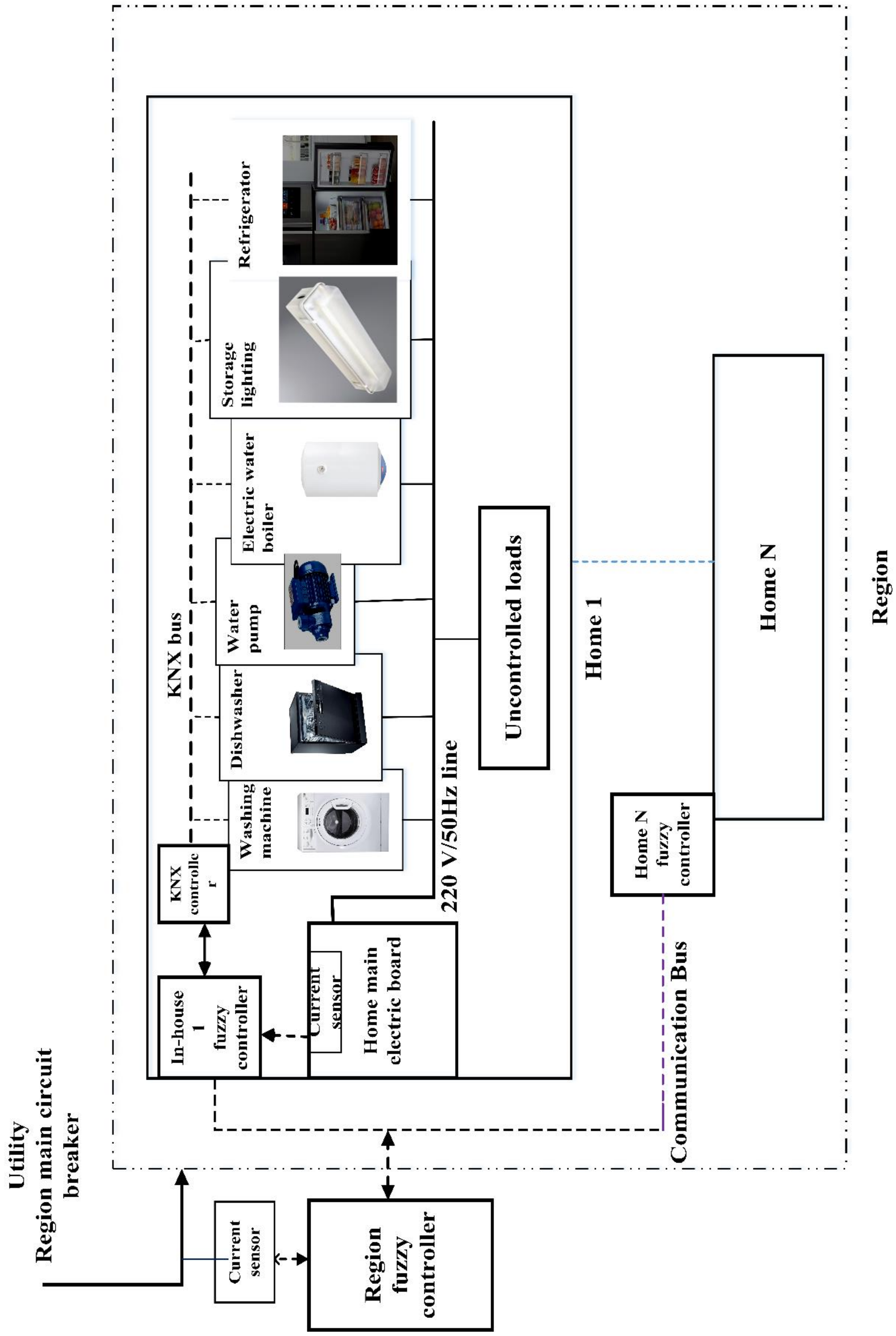


Figure 6.1:The Conceptual Block Diagram of the Fuzzy Control Strategy

6.3 Load Fuzzy Controllers Block Diagram

A fuzzy controller for a single house is designed to control and shift the operation of the loads. First, the fuzzy controller configurs each of the loads to ensure the shift of operation to off-peak hours. Then, all of the controllers are combined in a single in-house fuzzy controller. The layout of the controllers has common stages, shown in Figure 6.2.

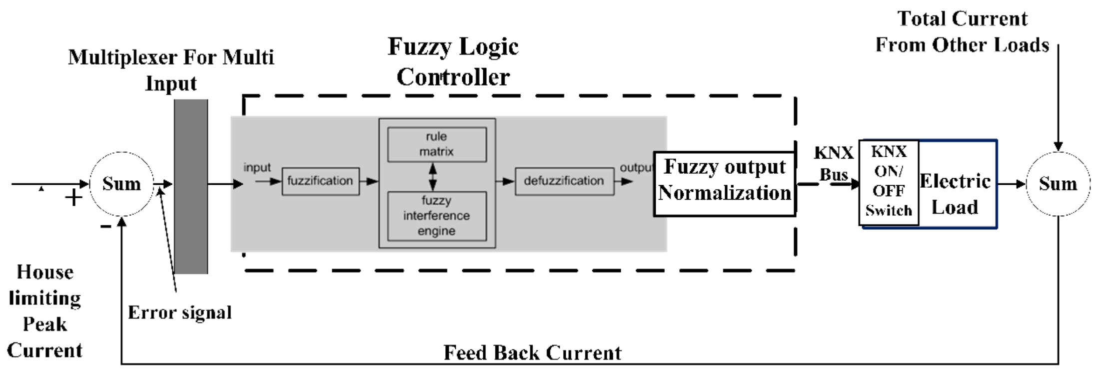


Figure 6.2: Load Fuzzy Controllers Blok Diagram

The main input to the load fuzzy controllers is the error signal, which is the difference between a predefined house peak limit and the measured feedback of house current consumption. Error and other appliance-related signals are fuzzed to linguistic variables that are assigned to triangular membership functions to specify their ranges. The input - output relationship of the fuzzy process are mapped out by use of "IF-THEN" rule sets. The center of gravity (COG) approach illustrated is used for defuzzification (Nguyen et al., 1995) of the fuzzy output to control signal.

$$COG = \frac{\sum_{i=1}^{m} \mu_A\ (x).x}{\sum_{i=1}^{m} \mu\ (x)} \tag{13}$$

Where, $\mu\ (x)$ is the fuzzy membership function set A and m is the number of IF-THEN rules assigned to the controller.

The output control signal is normalized to "on/off" signal such that it could be transferred by the KNX protocol and control the operation of the KNX switch for each electrical load.

6.4 Constraints of Domestic Electric Load Fuzzy Controllers

The fuzzy logic controller is used to reduce domestic peak loads. The instantaneous current consumption of each house is monitored by a current sensor positioned at the house electrical supply line. The "on/off" status of each domestic load is detected through KNX technology. The considered loads are expected to shift according to the following logic:

- Dishwasher and the washing machine operation could shifted to off-peak times only if they are in a standby mode. In other words, if the end-user requested these loads to operate during peak time, the controller interrupts this request and shifts the operation of these loads to off-peak times. However, if these loads are already in operation in peak times, the controller allows them to finish the operation cycle completely for interruption propels the electrical appliances restart the operation again, which means more consumption of washing liquid or powder and waste of money.
- The controller shifts the operation of electrical pumps in peak if the water in the rooftop storage tanks is or above the desired level.
- Electric boiler operation shifted in peak time if the water temperature is adjusted by the end-user.
- A storage lighting system is used during off-peak times, into which the controller releases signals to store electrical energy that could to used during peak times.
- The refrigerator setting point temperature could be lowered during off-peak times, and put back into normal setting points in peak times. Thus, refrigerators are programmed to operate less and save more during peak times by use the stored cooling energy during off-peak times.

6.5 KNX\EIB Technologies

KNX is an international communication protocol designed to be used in controlling intelligent buildings' electrical devices. As shown in Figure 6.3, all of the building's electrical devices, such as lighting, heating, cooling, air-conditioning, signalling, monitoring systems, metering, and audio/video systems, can be connected and controlled via the KNX bus (Zintech, 2015).

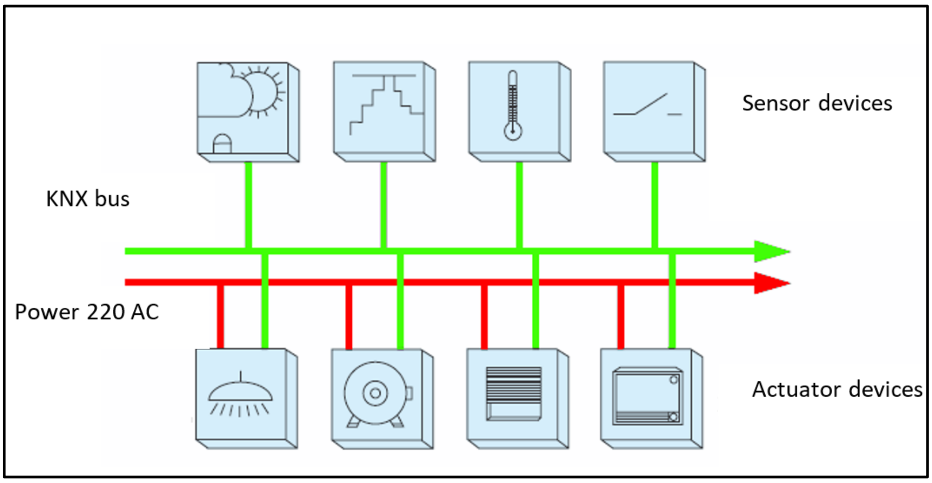


Figure 6.3: A Typical KNX Bus Network with Mixed Devices (Zintech, 2015)

6.6 Electric Load Fuzzy Controllers

6.6.1 Boiler Fuzzy Controller

The operation of an electrical water boiler is shifted by tracking three input signals shown in Figure 6.4. These signals are; the peak time, determined by the sign of the error; the boiler water temperature, which is signalled to the controller either from a temperature sensor or the boiler KNX temperature controller; and the end-user request order for the boiler, which can be tracked from the boiler's KNX switch. The sign of the error, the boiler water temperature, and the boiler request order input signals are fuzzed to linguistic variables, *"SignError"*, *"temp"* and *"Border"*.

The *"temp"* linguistic variable is divided into two ranges. One range indicates *"temp is Ok"* if the boiler temperature value satisfies the end-user, the other indicates *"temp is Not Ok"* if the boiler temperature value is lower than the end-user needs. The *"Border"* variable is divided into "*OFF"* and "*ON"* ranges. *"OFF"* means that the boiler is not requested by the end-user, and "*ON"* means the boiler is requested. "*SignError"* is divided into *"Yes"* and *"No"* ranges, *"Yes"* signals that it is a peak time , whereas *"No"* signals no peak time . The fuzzy controller is fuzzed to either to *"Start Boiler"* or *"Stop Boiler*" according to the settings of 8 fuzzy rules installed within the boiler's fuzzy controller. Table 6.1 provides a proper illustration of the rules.

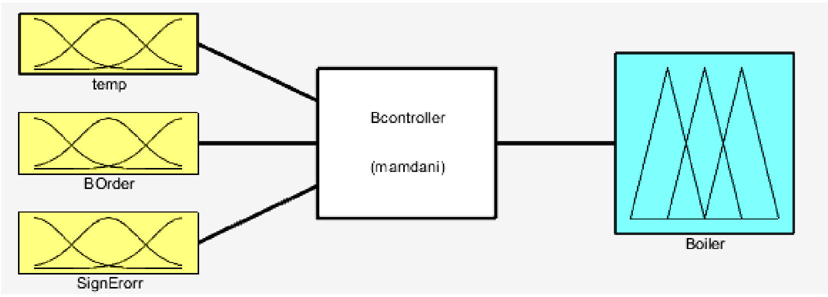


Figure 6.4: Boiler Fuzzy Controller

Table 6.1: Boiler Fuzzy Rules Set

1	*If (temp is NotOk) & (Border is BOoff) & (SignErorr is nv) then (Boiler is StopB)*
2	*If (temp is NotOk) & (Border is BOoff) & (SignErorr is pv) then (Boiler is StartB)*
3	*If (temp is NotOk) & (Border is Boon) & (SignErorr is nv) then (Boiler is StartB)*
4	*If (temp is NotOk) & (Border is Boon) & (SignErorr is pv) then (Boiler is StartB)*
5	*If (temp is Ok) & (Border is BOoff) & (SignErorr is nv) then (Boiler is StopB)*
6	*If (temp is Ok) & (Border is BOoff) & (SignErorr is pv) then (Boiler is StopB)*
7	*If (temp is Ok) & (Border is Boon) & (SignErorr is nv) then (Boiler is StopB)*
8	*If (temp is Ok) & (Border is Boon) & (SignErorr is pv) then (Boiler is StopB)*

The thermal isolation of the boiler mechanical structure helps storing the thermal energy for a long time. This construction enables the controller to shift the boiler to off-peak times, and always ensures the hot water is ready to use.

Spinks et al. (2006) suggest that the hot water temperature range from 55 to 65 °C is not effective to eliminate the formation of enteric/pathogenic bacterial species and recommends that the hot water boiler should operate at a minimum of 60 °C. Based on this recommendation, the ranges of temperatures assigned to membership functions of the boiler fuzzy controller shown in Figure 6.5

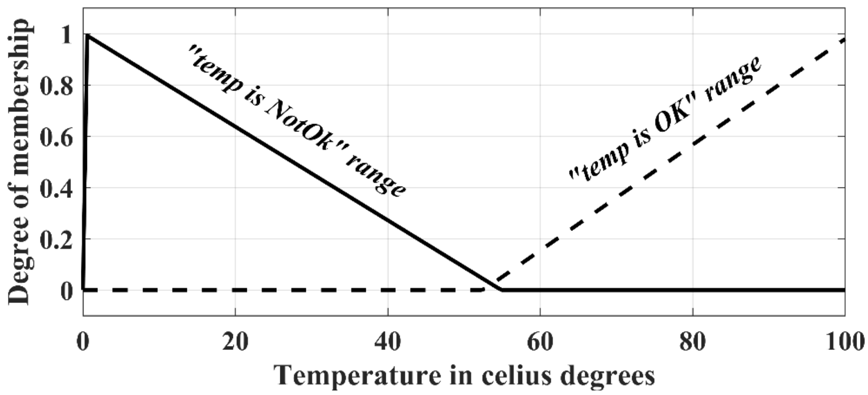


Figure 6.5: Boiler Fuzzy Membership Functions

6.6.2 Electric Pump Fuzzy Controller

Table 6.2 illustrates four fuzzy rules constructed to control the operation of the electric pump,. The input signals of the pump fuzzy controller are: the "*SignErorr*" and the "*waterlevel*" water level in the storage tanks. The peak and the off-peak signal "*SignErorr*" is handled in the same manner as boiler fuzzy controller. The water level signal *"waterlevel"* is assigned to *"waterlevel is Ok"* and *"waterlevel is NotOk"* ranges.

The pump fuzzy controller always ensures that the end-users water demand is fulfilled. The water quantity stored in the rooftop tanks makes possible the shifting of the water pump operation to off-peak times .

Table 6.2: Pump Fuzzy Rules Set

1	*If (waterlevel is Ok) & (SignErorr is nv) then (WaterP is StopWP)*
2	*If (waterlevel is NotOk) & (SignErorr is nv) then (WaterP is StartWP)*
3	*If (waterlevel is Ok) & (SignErorr is pv) then (WaterP is StopWP)*
4	*If (waterlevel is NotOk) & (SignErorr is pv) then (WaterP is StartWP)*

6.6.3 Washing Machine and Dishwasher Fuzzy Controller

The main issue with the controller is that it must not interrupt the washing machine and the dishwasher operation if they are already turned "on".

The rule base setting for the dishwasher is as the same as for washing machine , except in reality end-users usually request them to operate at different times. For the washing machine there are 3 input signals, namely, the sign of the error "*SignError"*; the end-user request command "*WMorder"*; and the washing machine's current operation status "*WMs*". "*WMs*" signal is divided into *"ON"* fuzzy range, which means, the machine is currently in operation, and *"OFF"* fuzzy range, which means, the machine is not currently in operation. The sign of the error signal is treated as the previous controllers. "*WMorder"* is assigned to *"Yes"* range, which means, the machine is requested by the end-user, and to *"No"* range, which means, the machine is not requested. The output of the washing machine fuzzy controller is divided into the *"Stop washing machine"* and *"Start washing machine"* fuzzy ranges.

Table 6.3 presents the rules that govern the operation of the washing machine controller. The washing machine is kept "on" during either peak or off-peak time to finish the operation cycle if it is currently in operation. If the washing machine is not currently in operation the controller shifts the operation once it is requested by the end-user, peak time .

Table 6.3: Washing Machine Fuzzy Rules Set

1	*If (SignErorr is nv) and (WMorder is wmOoff) and (WMs is offwm) then (WashingMachin is stopWM)*
2	*If (SignErorr is pv) and (WMorder is wmOoff) and (WMs is offwm) then (WashingMachin is stopWM)*
3	*If (SignErorr is nv) and (WMorder is wmOoff) and (WMs is onwm) then (WashingMachin is stopWM)*
4	*If (SignErorr is pv) and (WMorder is wmOoff) and (WMs is onwm) then (WashingMachin is stopWM)*
5	*If (SignErorr is nv) and (WMorder is wmOon) and (WMs is offwm) then (WashingMachin is stopWM)*
6	*If (SignErorr r is pv) and (WMorder is wmOon) and (WMs is offwm) then (WashingMachin is starWM)*
7	*If (SignErorr is nv) and (WMorder is wmOon) and (WMs is onwm) then (WashingMachin is starWM)*
8	If (SignErorr is pv) and (WMorder is wmOon) and (WMs is onwm) then (WashingMachin is starWM)

6.6.4 Lighting System Fuzzy Controller

A storage lighting system is popularly used as a backup whenever a cut-off occurs in the domestic electrical supply. This system is set to manage houses' lighting demands. The assigned fuzzy rules control the storage during off-peak times so that it is ready to use as a backup or substitute for lighting whenever the end-user decides. The rules shown in Table 6.4 depend on the sign error signal "*SignError"* as the input signal of the controller.

Table 6.4: Storing Lighting System Fuzzy Rules Set

1	*If (SignErorr is nv) then (Storing is StoringON)*
2	*If (SignErorr is pv) then (Storing is StoringOFF)*

6.6.5 Refrigerator Fuzzy Controller

Two fuzzy rules are used to implement this control strategy. The rules depend on the sign error signal "*SignError"* as the input signal of the controller (see Table 6.5). If the "*SignError"* is negative, this means peak consumption then the output of the fuzzy controller shows *"HighTemp"* signal, which rests the required temperature to a high value between 4 to 6 C°. While if the "*SignError"* is positive, which means no peak consumption, the output of the fuzzy controller shows *“LowTemp”* signal, which rests the required temperature to a lower value between 0 to 2 C°. These temperature values could be changed and adapted according to the end-user need . Setting the required temperature to a low value makes the refrigerator operate for longer time compared to a high value.

Table 6.5: Refrigerator Fuzzy Rules Settings !!

1	*If (SignErorr is nv) then (Ref is ONatLowerTEMP)*
2	*If (SignErorr is pv) then (Ref is ONatHighTEMP)*

Therefore, depending on the thermally isolated design of the refrigerator, it efficiently reduces the electrical demand of peak hours. During off-peak times the refrigerator fuzzy controller resets the operation temperature to a lower value than the average use. During peak times, it resets temperature to a higher value. The stored cooling energy, particularly, during long off-peak hours, reduces the refrigerator’s “on” time.

6.7 In-House Fuzzy Controller

All the fuzzy rule sets for the boiler, the pump, the dishwasher, the washing machine, the storage lighting system, and the refrigerator fuzzy controllers are combined to form the fuzzy rules set of the in-house fuzzy controller. The input and the output signals of the in-house fuzzy controller are the input and the output signals of the electrical load controllers. Therefore, the in-house fuzzy controller is a multi-input-output-system.

In-house fuzzy controller continuously measures the total house consumed current, shown in Figure 6.2, and prevents the current exceeds the predefined value of the house peak limit . For example, if e the appliances in the house are all turned on at the same time and the house consumed current does not exceed the peak limit then the controller does not act. however, if it exceeds then the in-house controller applies the designed fuzzy rule set to curtail the excess of the house consumed current.

Mostly, the controller turns on the six load collectively during off-peak time, and this happens only if their consumed sum up current value does not exceed the value of the house peak limit current.

6.8 Region Fuzzy Controller

The main purpose of the region fuzzy controller is to reduce the region's peak loads. Such peaks happen if all the in-house fuzzy controllers shift some or all of the loads atsame time. The input signals for the region controller are the following: the error signal, which is the difference between a predefined region peak limit current; and the instantaneous measured value of the region consumed current; and the communicated signal from each house of the instantaneous consumed current value in real time. The configuration of the region controller shown in Figure 6.6.

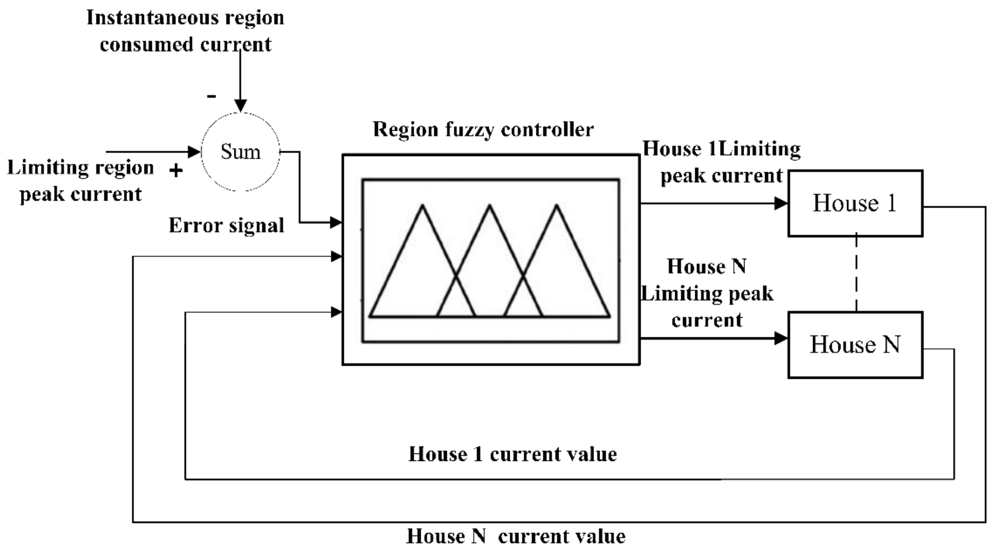


Figure 6.6: Conceptual Drawing of the Region Fuzzy Controller

The error signal takes either a positive value or negative value. The positive means that a region peak is not occurring and negative means that region peak is occurring. The input signals from the houses inform the region controller of the houses' current value. The inside house consumed current is assigned to a triangular membership function, shown in Figure 6.7. One function is for the small current values, chosen as any current value between 0 and 7, and the other is for the large current values, chosen as any current value between 5 and 16. These values are liable to change as required by the utility or based on the total region peak limit current.

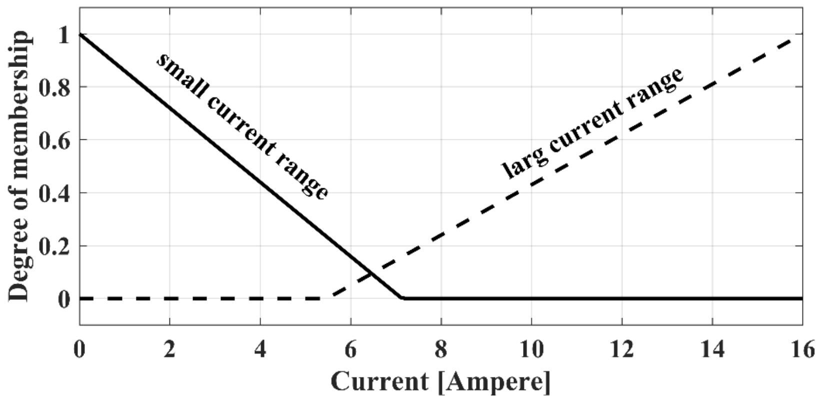


Figure 6.7: Membership Functions Assigned to Determine Each House Peak Current Range

The outputs of the region fuzzy controller are manipulated through a fuzzy rule set. The output for each house is the value of the house peak limit current . The houses' peak limit current values are determined according to region controller output assigned membership functions shown in Figure 6.8. This value propels in-house's fuzzy controller decides whether or not a load shifting is necessary and what loads shift at any particular time. Figure 6.7 illustrates the the contrast between the current value in one house that is within the small range and another house that is within the large range. In the case of the house with the large range current value, based on its output member functions (Figure 6.8) the region controller assigns a high peak limit current value . In the case of the house with small range current value, the region controller fuzzy rules determines that the peak limit current value is a value equal to a current value assigned from the low or medium current ranges (Figure 6.8). In such case, the house with the higher peak limit current value does not need to shift as many loads as the house with the low peak limitcurrent value.

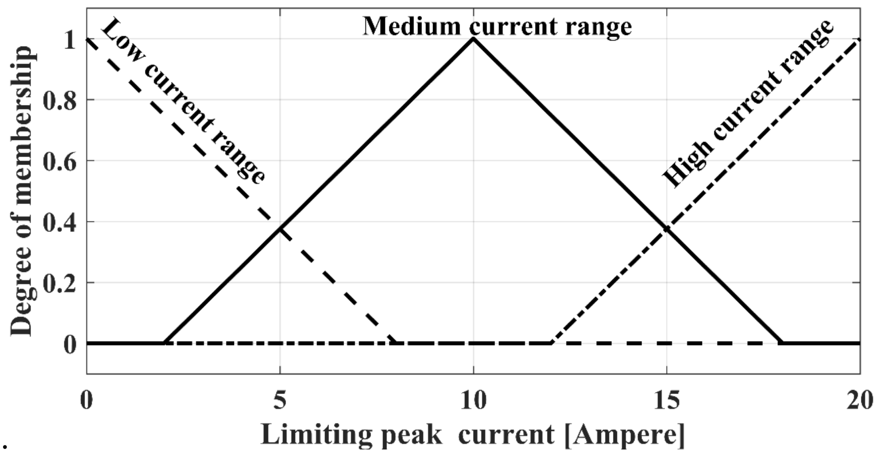


Figure 6.8: Region Controller Assigned Output Membership Functions

The unequal values of houses' limiting peak currents lead to the shifting of different loads to off-peak time and achieve the fairness of power demand between the region occupants. As stated before in section 6.8.2 the maximum load current in the case of Palestine is 25 Ampere. Therefore, this value is the maximum limiting peak current assigned by the region controller. Moreover, limiting peak current values do not affect the operation of uncontrolled domestic loads, they limit the operation of the loads by the in-house controller. These values could be changed to suit the utility peak power reduction and to suit the region allowed maximum current.

6.9 Results and Discussion

6.9.1 House Fuzzy Controller

The simulation result of the in-house fuzzy controller shown in Figure 6.9 is obtained under the constraints of the operation scenario listed in Table 6.6. The boiler water temperature and the water level are assumed “Ok” for the whole simulation period. Table 6.6 in the last column lists the in-house fuzzy controller responses to this scenario shown in Figure 6.10 and Figure 6.9.

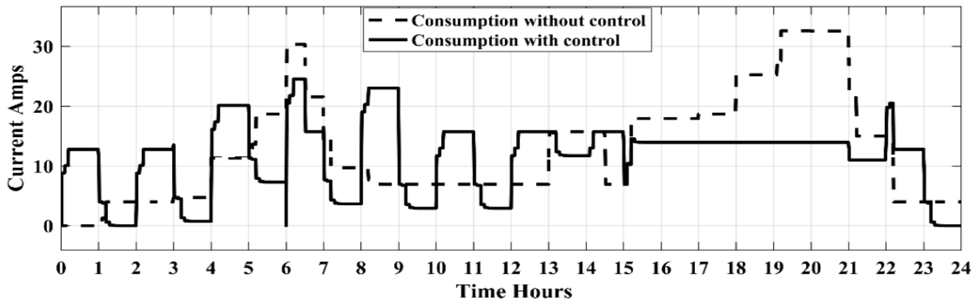


Figure 6.9: House Current Profile with and without Applying In-House Fuzzy Controller

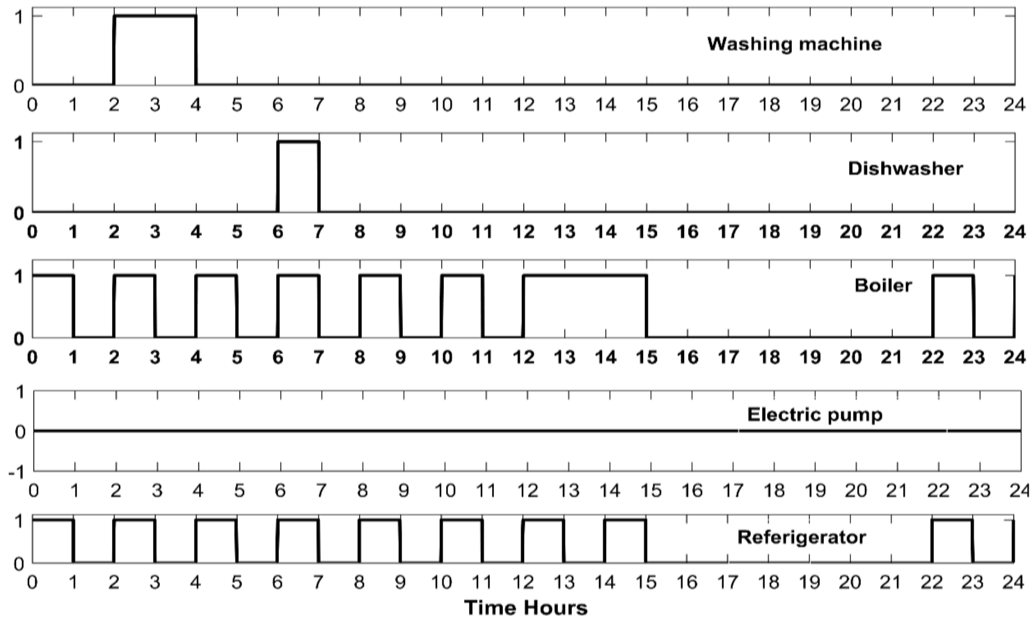


Figure 6.10: In-House Fuzzy Control Normalized Output

Table 6.6: Operation Scenario Example and the In-House Controller Responses

Electrical loads	Requested Operation Time Periods	Fuzzy Controller Responses
Dish Washer	From 2 AM - 5 AM and from 4 PM -7 PM	Shifted from the period 4 PM -7 PM to the period 2 AM - 5 AM
Washing Machine	From 5 AM -7 AM and from 7 PM -9 PM	Shifted from the period 7 PM-9 PM to the period 5 AM -7 AM
Water Pump	From7 AM – 8 AM	Turned off for the whole simulation period
Boiler	From 1 PM – 2.5 PM	“on” whenever off-peak times existed
Lighting	From 6 AM - 9 pm	No action
Air Condition	From 3 pm – 10 pm	No action
Iron	From 6 AM – 6.5 AM	No action
Refrigerator	Assumed always “on”	

6.9.2 Region Fuzzy Controller

To demonstrate the operation of the region controller, a region contains that three houses is considered as an example to test the performance of the region controller. The maximum allowed current for each house is 25 Amperes. If any of these houses consumed current exceeds this value, the in-house automatic circuit breaker installed by the utility cut off the house supply current. An average current value of 12 Amperes is considered as the house limiting peak current. By Multiplying this value by three then the limiting peak current for the considered region in this example is 36 Amperes.

As an example, let us assume the same loads with the same operation scenario for the three houses. If the region controller is alarmed of a region peak is looming , then it signals the three in-houses’ controllers with the values of their limiting peak currents to do their works. These values are determined based on each house consumed instantaneous current value. For example, if the region controller finds that the current values in the second and the third house are small, then the region controller signals house 1 to do its job based on a low value of house limiting peak current.

The performance of the region controller is tested based on a sample of three houses assumed to work with the same operation scenario. The consumed current profile after the joint control work between the region controller and the in-houses' controllers as observed in Figure 6.11 is smoother than the profile before control. In addition, due the developed control strategy, he distribution of the consumption is seemingly much better. .

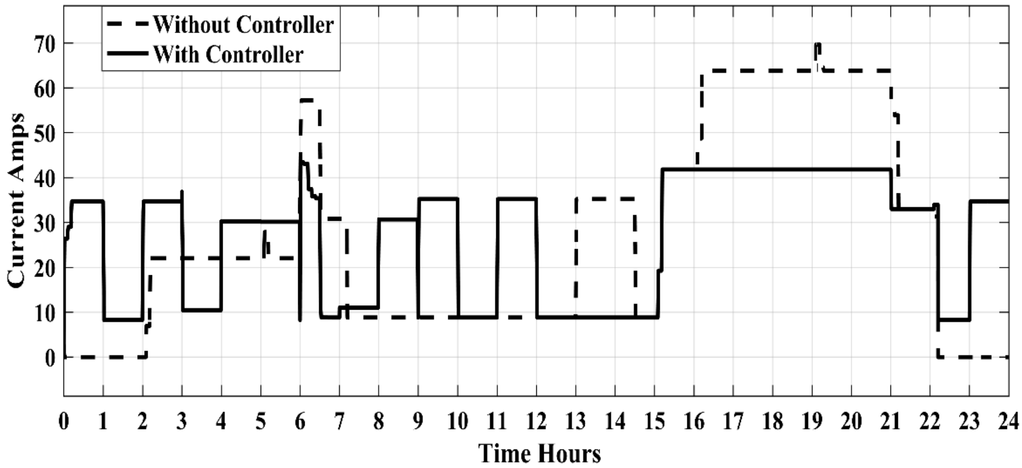


Figure 6.11: Current Profile before and after Applying Region Controller for a Sample of Three Houses

The region controller assigns the limiting peaks based on its fuzzy rule sets. These rules consider the instantaneous consumed current in all houses within the controlled region. For example, Figure 6.12 and Figure 6.13 show that during the period from 15:00 to 16:00 the limiting peak current of house 1 value was 7 Ampere (Figure 6.12). This value is because House 1 consumes high current which is about 25 Ampere during the same period. House 2 limiting current is 18 Ampere because of the low consumed current of 8 Ampere, while the limiting current of House 3 during the same period is 7 Ampere because of the consumed current of 18 Ampere.

Figure 6.12 and Figure 6.13 conclude that the region controller is effective, but such effectiveness could be at stake if a large number of houses are encountered. The work of the region control depends on real-time communicated data. In general, a delay in these real-time communications may occur and thus this negatively affect the robustness of the region controller. This problem can be solved if the proposed control strategy is implemented of nearly distanced houses with a local communication network.

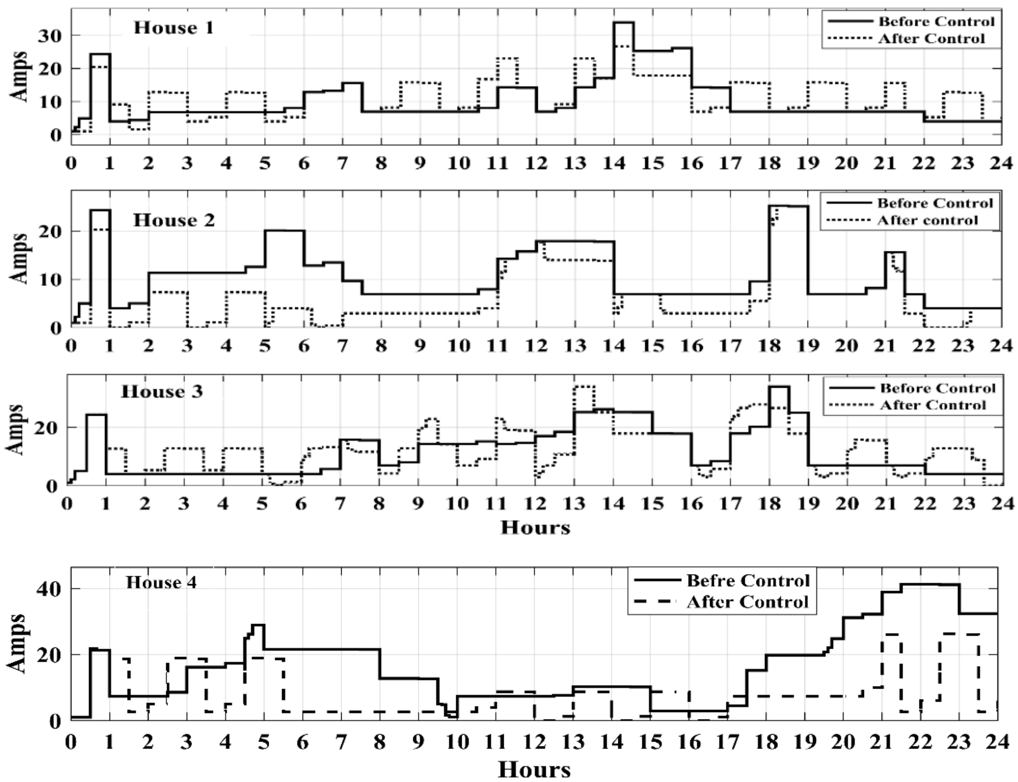


Figure 6.12: Current Profiles before and after the Joint Control Work of the In-House and the Region Controller

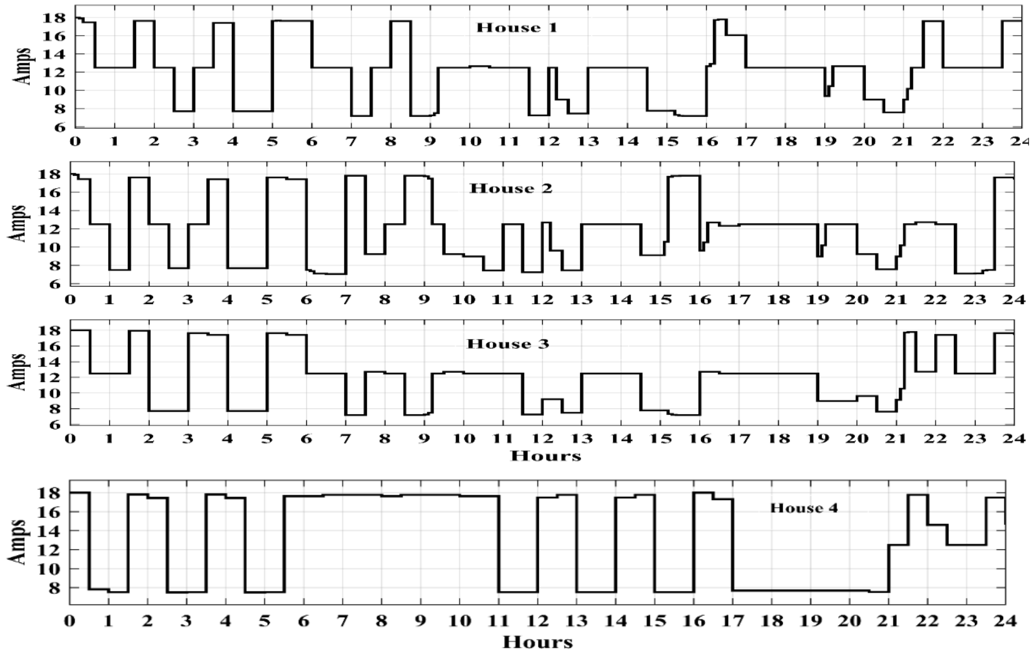


Figure 6.13: Limiting Peak Currents Assigned by the Region Controller for the Houses in Figure 6.12

6.10 Control Strategy Validation

A comparative study is conducted by Chandran et al. (2016) between direct control load (Boolean logic) and fuzzy logic control in modifying consumer peak power consumption. It proved that the Boolean logic controller reduces the consumer peak power consumption at the expense of the consumer's comfort level. It also states that the fuzzy logic reduces the end-use peak power consumption but at the same time preserves the thermal comfort level of the consumer because of its capability of including non-deterministic variables like the comfort level.

Chandran et al. (2016) introduces a demand response program utilizing direct domestic fuzzy load control approach. The similarities and the differences between Chandran et al. (2016) strategy and the fuzzy logic developed direct control strategy introduced in this research shown in Table 6.7. It could be noticed from the table that the closed-loop developed direct control approach, increases the reduction percentage of peak power consumption by 3% compared to Chandran et al. (2016) controller. Chandran et al. (2016) reduces peak energy at the expense of the occupants comfort level while the controller developed preserves occupants comfort.

Table 6.7: The Differences and the Similarities between the Developed and Chandran et al. (2016) Fuzzy Control Strategies

Item	Chandran et al. (2016) Strategy	This Research Strategy
Control Approach	Open-loop Direct load switching "on/off" based on day a head electric tariffs through scheduling the operation of the loads and operate the scheduled loads during low price tariff (off-peak times)	Closed-loop direct load switching "on/off" based on the difference between the value of the instantaneous house consumed current and the predefined value of the in-house peak limit current. Controlling is achieved through shifting the load operation during off-peak times
Fuzzy Controller Performance Testing Software	Matlab	Matlab
Domestic Loads Modelling	Allowable load schedule	Developed Matlab/Simscape load model
Controller Inputs	Time of the day, load demand, inside-house temperature deviation, occupants availability	Instantaneous inside-house measured current, rooftop tank water level, Boiler temperature, Inside-refrigerator temperature, controlled operation statuses, predefined limiting peak current.
Controlled Loads	TV, Washing Machine, Heating, computer, water pump	Washing machine, dishwasher, boiler, water pump refrigerator, storage lighting system
Occupants Comfort	Thermal comfort preserved	Thermal, water consumption, laundry, cooking
Peak Energy Reduction	Peak load is reduced by about 40%	Peak load is reduced by about 43% (Figure 6.11)

6.11 Chapter Summary

The proposed control strategy has proved to be an efficient method to avoid power consumption during peak hours. The human comfort level is taken into consideration, and this is noted within the set of fuzzy controller rules. Within the strategy, the fuzzy controllers integrated with KNX technology are assigned to control the domestic appliances. As KNX technology is not widespread in developing countries, simple relay circuits could be used instead of controlling the appliances with “on/off” commands. Several operational scenarios are tested where the controller effect of avoiding certain current peaks is achieved.

Chapter 7

IMPACT OF PEAK LOAD MANAGEMENT STRATEGIES

7.1 Introduction

The control strategies developed in chapter 4 and 6 installed as a part of Demand-Side Management (DSM) strategy. The environmental, the stability of the distribution electrical grid (diversity and the load factors), and the economic impacts of these strategies are the subject of this chapter.

7.2 Impact on The Distribution Electrical Grid: Diversity and Load Factors

7.2.1 Pumping Control Strategy: The Modelling of Random Pumping

Figure 4.1 clearly shows that pumping is under the constraint of the existing control scheme . The existing control scheme "on/off" pump cycle ranges between a water volume of 950 L to 1000 L with a pump capacity of 746 watts and a flow rate equal to $\dot{Q}_{pum}$ =2773 L/h at a head of 4 m. Hence, a sampling time of T=1 sec is chosen to detect accurately the water pumping occurrences each time during the day. The rooftop tank water volume at any sample time is estimated in Eq. (14), and the pump control operation switch S (see Figure 4.1) status is formulated in Eq. (15)

$$V(KT+1) = V(KT) + S(KT) \times V_{pum} - V_{con}(KT) \tag{14}$$

$$K = 1,2,3 \dots \dots \dots n = 86400$$

Where, $V_{pum}= \dot{Q}_{pum} \times T/3600$ in L

$V_{con}(t)$ is the water volume consumption at time sample KT in L

$$S(KT)\ \ either\ [0,1]\ at\ each\ sample\ time\ \ KT \tag{15}$$

Where,

$S(KT) = 1\ if\ V(KT + 1) \leq 950\ L$

$S(KT) = 0\ if\ V(KT + 1) \geq 1000\ L$

From Eq. (15) the existing control scheme automatically turns the pump "on" to refill the rooftop tank if the water volume in the tank drops below 950 L. Assuming normal operation conditions (no water or electricity outages), the existing control scheme always maintains the rooftop tank water volume at a maximum value of 1000 L. Based on these equations, the algorithm shown in Figure 7.1 is developed to model the random water pumping works. The algorithm generates a random number **(r)** to indicate the water consumption starting time. The value of (**r)** could be any sample time number **(KT)** during the day. The statues of the starting pumping switch $\boldsymbol{S}(\boldsymbol{KT})$, either ("on"=1) or ("off"=0), is determined by the water level in the rooftop tank. As a result, when the algorithm operates for sample **(N)** number of houses, the pumping overlap increases drastically as the number of the houses increase.

The output of this algorithm is two matrices: $\boldsymbol{SW}$ is the pump switch statues matrix which records the pump switch ***S (KT)*** statues "0 or 1" at each sample time during the day; and $\boldsymbol{ST}$ is the sample time matrix which records the time duration value at which the pump switch is "1". These matrices are represented by Eq. (16) and Eq. (17).

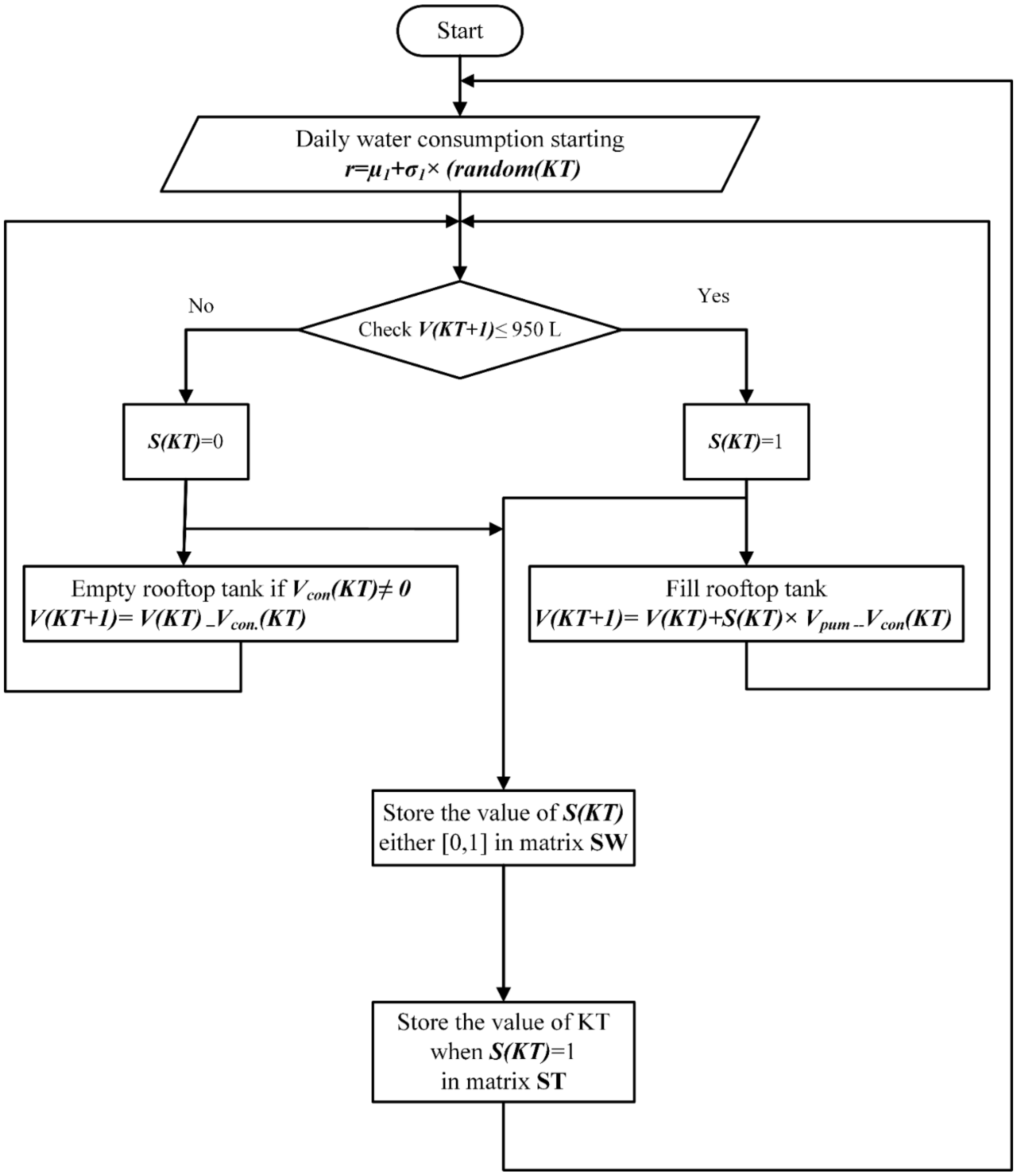


Figure 7.1: Pump Operation Algorithm under Constraints of the Existing Control Scheme

$$\boldsymbol{SW} = \begin{bmatrix} 0\ or\ 1 & \cdots & for\ house\ 1 \\ \vdots & \ddots & \vdots \\ 0\ or\ 1 & \cdots & for\ house\ N \end{bmatrix} matrix\ dimension\ is\ (i = N) \times (j = K) \tag{16}$$

$$\boldsymbol{ST} = \begin{bmatrix} 0\ or\ t_1 & \cdots & for\ house\ 1 \\ \vdots & \ddots & \vdots \\ 0\ or\ t_{KT} & \cdots & for\ house\ N \end{bmatrix} matrix\ dimension\ is\ (i = N) \times (j = K) \tag{17}$$

Each row in $\boldsymbol{SW}$ matrix represents the number of times the pump switch is "0 or 1" for a particular house, and each column in $\boldsymbol{SW}$ matrix shows how many pumps are "on" in that particular sample time. Each row in $\boldsymbol{ST}$ matrix refers to the time duration value of a particular house when the pump is "on", while each column represents the pumps overlap, i.e, how many pumps are "on" at the same sample time.

The number of the overlapped houses (N_{ol}) at a given sample time could be calculated:.

$$N_{ol} = \left(\sum_{j=1}^{KT}\sum_{i=1}^{N} SW(i,j)\right) \tag{18}$$

Where, (N_{ol}) is the number of the "on" pumps a at that sample time

KT=1, 2, 3..... is the end of the required period during the day

7.2.1.1 Random Pumping Assumptions

Figure 7.1 elucidates that the daily peaks hours and the daily water consumption profile are essential for investigating the random pumping work by use of the algorithm . Figure 7.2 shows t he typical hourly average of domestic daily hot water demand profile in winter time for N. Cyprus. The profile is estimated by Kalogirou, (2009) for 4 occupants' family in N. Cyprus. Figure 7.2 concludes that the high water consumption concentration is in two time periods. The first period is from 6:00 AM to 12:00 PM and the second period is from 16:30 PM to 22:30 PM. These periods when most of the family members either awake in the morning, take showers and prepare themselves to go for their daily duties, or return home in the evenings from work, take showers and rest.

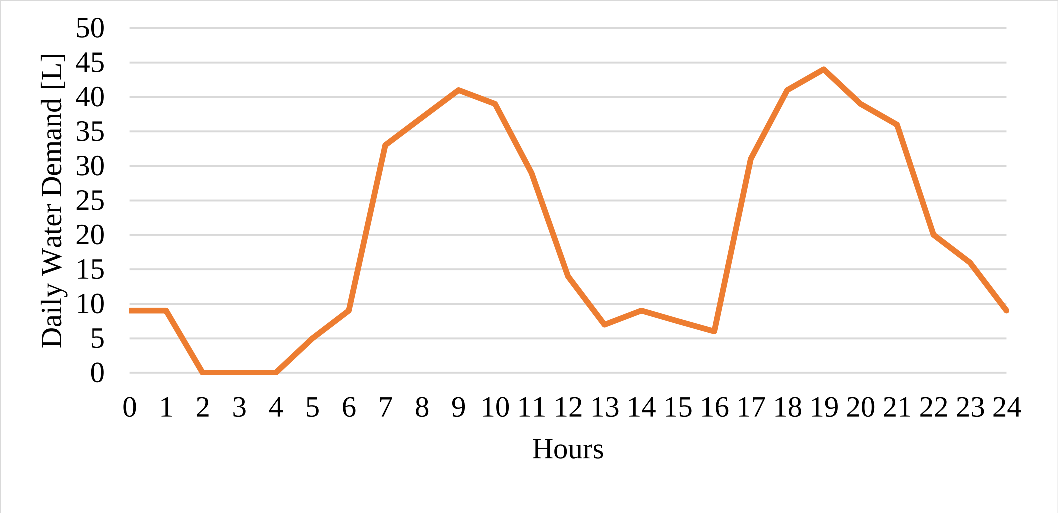
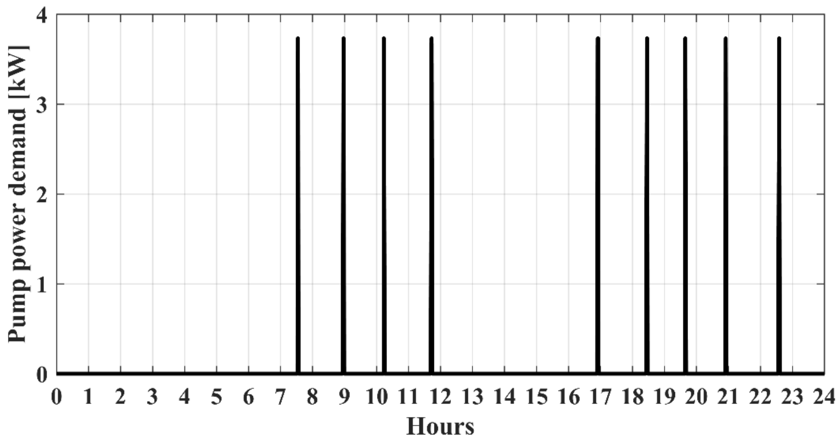


Figure 7.2 Hourly Average Domestic Daily Water Demand Profile for a Single House in N. Cyprus (Kalogirou, 2009)

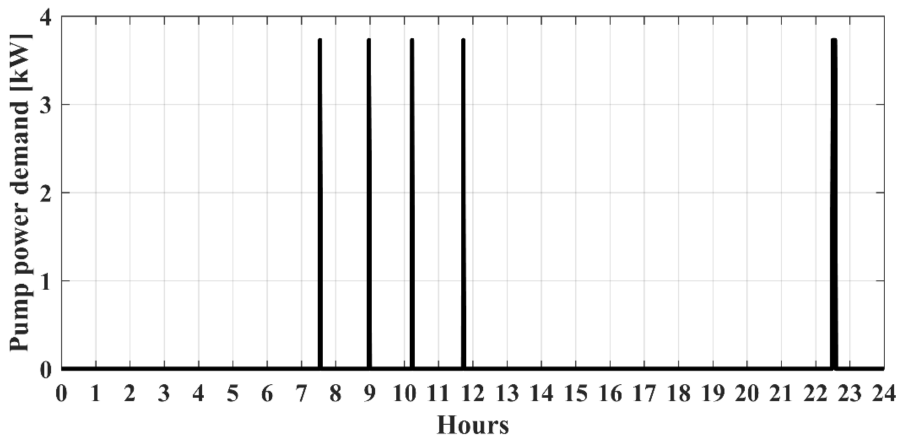
Figure 4.6 shows the peak hours power demand obtained for N. Cyprus in two typical summer and winter days in June and January in 2012. The country summer peak hours are from 9:00 AM to 19:00 PM and winter peak hours are from 16:30 PM to 22:30 PM.These hours represent the peak power demand which are above the summer and winter base demand lines shown in Figure 4.6. However, the geometric shape of these two periods can be represented by the random normal distribution with mean values of($\boldsymbol{\mu_1}$) and ($\boldsymbol{\mu_2}$) and standard deviations values of ($\boldsymbol{\sigma_1}$) and ($\boldsymbol{\sigma_2}$) respectively**.** Then the pumping distribution during a day for a randomly selected sample of houses should follow these two periods. Based on these assumptions, a normal random distribution number ($\boldsymbol{r}$) (see Figure 7.1), which represents the starting time of the daily water consumption of each house, is obtained to randomize the pumping work. The random ($\boldsymbol{r}$) value is constrained to randomly start each house daily water consumption at any sample time during the first peak consumption period. The first high water consumption period is chosen to determine the distribution of the pumping and the maximum possible pumping number of times during peak electric power demand.

7.2.1.2 The Impact of Pumping Control Strategy on Diversity and Load Factors

The water level modified controller introduced in chapter 4 is adjusted to track the wintertime peak hours. As a consequence of the new adjustments, Figure 7.3 proved that the controller succeeds in preventing the pumping works during winter peak hours.



(a)



(b)

Figure 7.3 Pumping Distribution of One House in One Day, a) Before the Implementation of the Controller Developed, b) after the Implementation of the Pumping Controller in Winter Time.

Despite the increase of the overlapped pumping work with the increase of the houses number, the controller eliminates the pumping work during peak hours. For example, the dashed line in Figure 7.4shows the random pumping work of 25000 houses, where the controller eliminates the pumping from16:30 PM to 22:30 PM . This period completely coincides with the country winter peak hours power demand (see Figure 4.6).

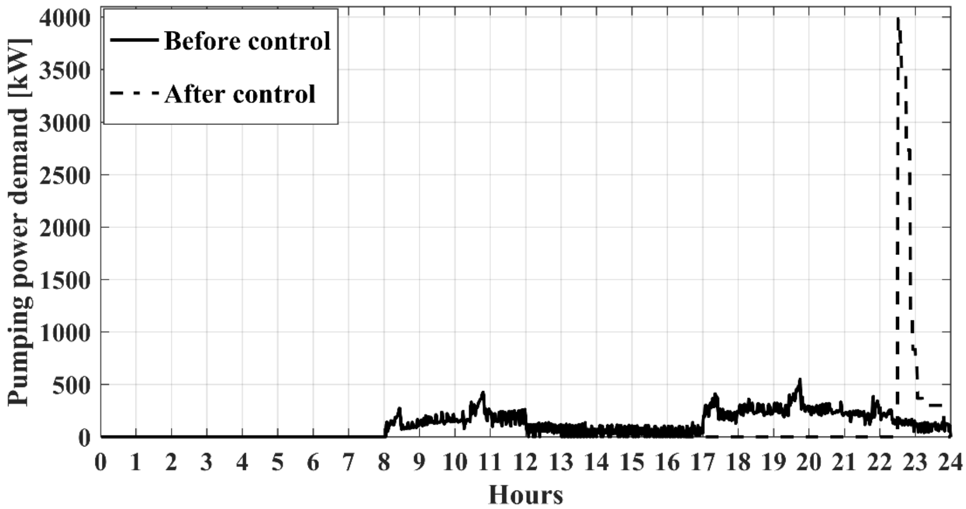


Figure 7.4 Random Pumping Works of A Number of Houses Equal to 25000 before and after The Implementation of The Pumping Controller

Unfortunately, the controller shifts and concentrates the pumping power demand during off-peak hours from 22:30 PM to 24:00 PM. This problem affects negatively the diversity and the load factors of the distribution electrical grid. The diversity factor is the ratio of the summation of individual maximum demands to the maximum peak demand, its typical value should be greater than one. However, the increased maximum peak between 22:30 PM and 24:00 PM decreases the diversity factor assuming constant individual maximum demands. The load factor is the ratio of the average demand to the maximum peak demand, its typical value is equal to one. The increased maximum peak problem decreases the load factor assuming constant average demand. The decrease of these factors increase the cost of power generation.

The solution for this problem is by distributing the pumping works during the period between 22:30 PM to 3:00AM such that this period coincides with the low water consumption period (see Figure 7.2). In other words, this problem could be solved by time scheduling of the pumping works. For instance, each of the included houses is scheduled to operate its pump at a random sample time from 22:30 PM to 3:00 AM. The pumping in each house is scheduled according to the algorithm shown in Figure 7.5. This part is a new modification of the modified control algorithm developed in chapter 4.

The distribution algorithm shown in Figure 7.5 preserves the end-users comfort level. For example, despite of the scheduled time of a particular house, if the water level in the rooftop tank of that house is under the h_peak (see Figure 4.3) the pump operates to preserve the house water supply. If the water level is below h_ref the controllerstarts the pump only if the real world sample time matches the random scheduled sample time in the house. As shown in Figure 7.6, the schedule algorithm solved the problem elaborated in Figure 7.4,evidently the pumping works are distributed during the considered off-peak period.

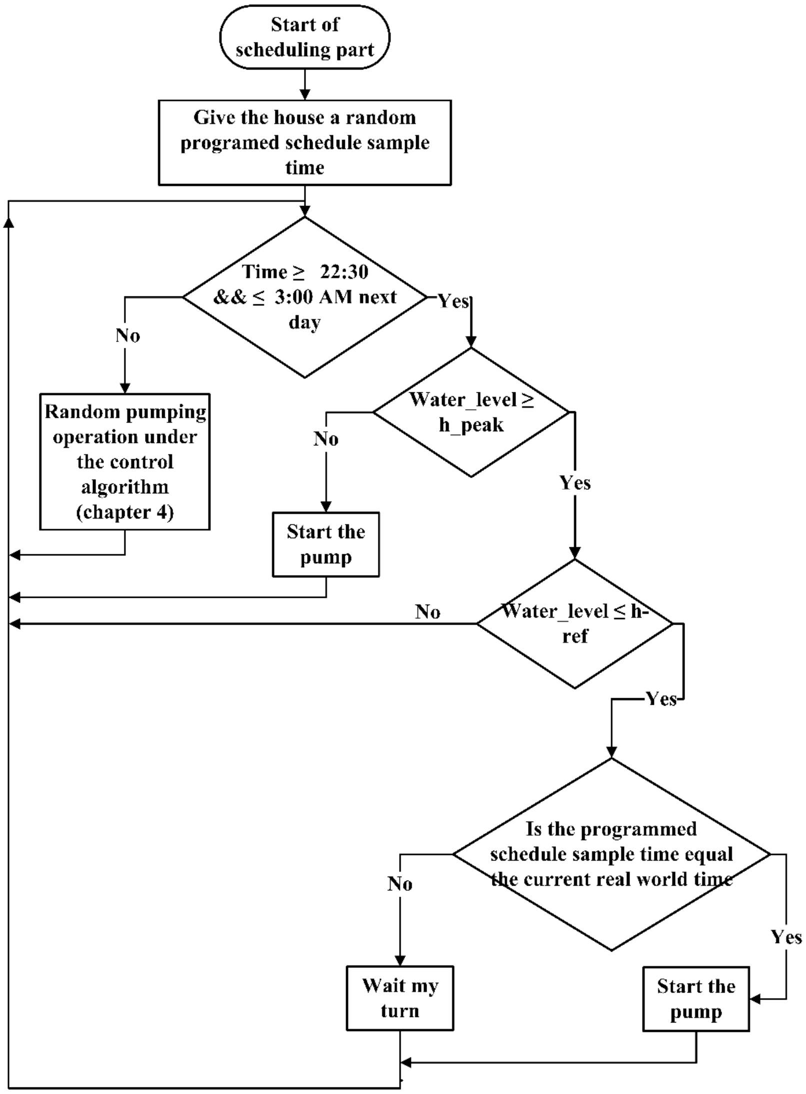


Figure 7.5 Pumping Works Scheduling Algorithm

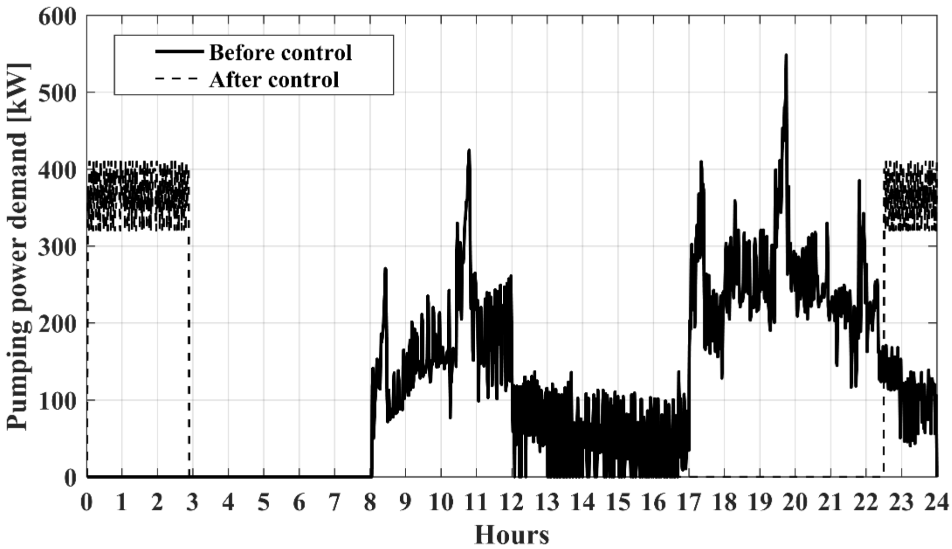


Figure 7.6 The Distribution of the Pumping Works of Figure 7.4 after Running the Scheduling Algorithm

7.2.2 Fuzzy Control Strategy Impact on Distribution Electric Grid

Jabir et al. (2018) conduct a review study about the impact of DSM programs on electrical grids. From this study, Aghaei et al. (2016) prove through using linear programming optimization technique that DSM programs achieve voltage stability. DSM programs also maintain electrical grid frequency stability (Babahajiani et al., 2016). These benefits is achieved if the DSM is a load distributive program.

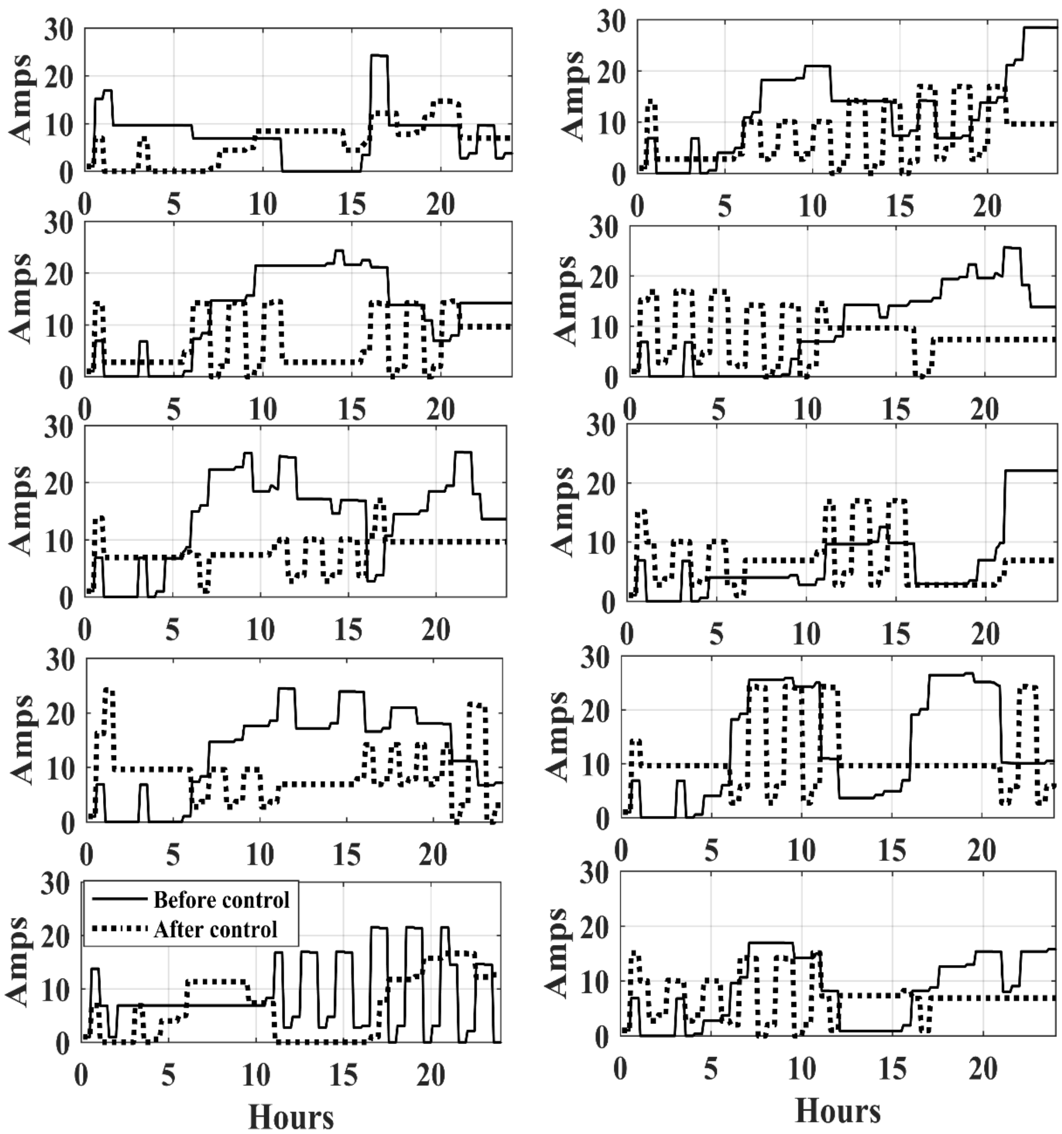


Figure 7.7: Current Consumption before and after the Implementation of the Fuzzy Control Strategy of a Sample of Houses with Random Operation Scenarios of the Electrical Loads

After conducting simulation for 40 houses, Figure 7.7 shows that the fuzzy developed load management controllers are distributive load shifting . Such that, the region controller monitors both, the region total current consumption and the individual houses . Based on the received limiting peak current value, the in-house controller manages the operation times of the controlled loads. The management occurs in a condition when the house current consumption value does not exceed the limiting current value at any time during the control horizon. Therefore, there is no chance for a group of the controlled loads to operate collectively if the summation of the currents exceeds the limiting current at that particular instant. More importantly, it must be reminded here that, the region controller continues to s signal the houses with the limiting current values at all the time; peak and off-peak hours .

The simulation results for a large number of houses (Figure 7.7 shows a sample of 10 houses) gave evidence that the fuzzy controllers' operation has a low probability to negatively affect the diversity and the load factors of the electric distribution grid. Figure 7.7 shows that the operation times of the loads are distributed along the control horizon with a low maximum peak value compared to the consumption without control.

Utilities try to achieve 3-phase balance by equally distributing the loads among the phases. The Phase balance in the residential sector is challenging because of the random operation of the residential loads (Moradzadeh & Tomsovic, 2013). Safdarian et al. (2014) argues that most of DSM programs does not take power system constraints such as grid stability, distribution lines capacity and other constraints into consideration. Safdarian et al. (2014) proposes the solution that the limits of the constraints are better to be preserved by the utility company. Unfortunately, in developing countries where conventional grids are still in use, this solution may not be applicable because of the lack of data exchange between demand and supply sides.

The fuzzy control strategy in this research could be expanded to accommodate these constraints. The conceptual diagram shown in Figure 7.8 presents the idea of this development. It is based on the work of Moradzadeh and Tomsovic (2013), however, remoulded in a practical way. The idea is that the 3-phase imbalance should be preserved within the designed limits and the flow capacity of the distribution lines should not exceed the maximum limit designed by the utility.

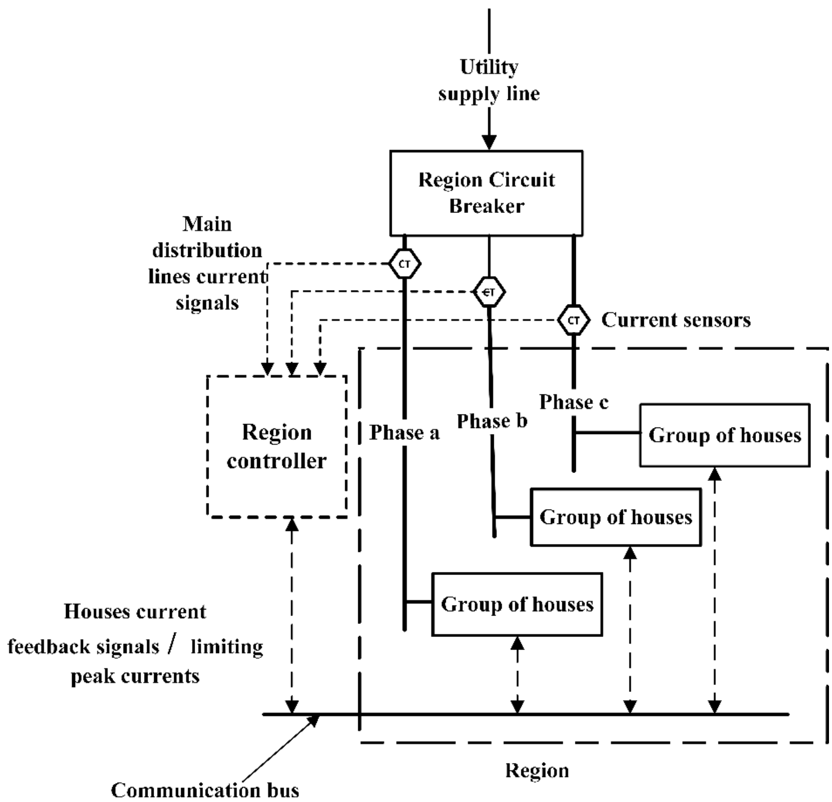


Figure 7.8: The Idea of the Fuzzy Control Strategy to Preserve Grid Stability

This can be achieved by measuring the flowing current in each phase individually. Besides, the houses should be classified according to the phase they are connected to. Based on the measurements of the phases current, the region controller can do the required calculations of the imbalance and the flow capacity limits. Depending on the results of these calculations, the region controller determines the limiting peak current values which ensures the stability of the grid. The basis upon which the current values is determined rests on the phase imbalance and the flow capacity required limits. Further work on this ideais highly recommended for future research.

7.3 Economic Impact of Control strategies

A DSM program can be proposed based on the control developed strategies in this research. If the utility does not choose to invest in the peak demand reduction control strategies. Then the utility needs to purchase a peak backup generator with a capacity equivalent to the load reduction capacity achieved by the control strategies developed. The load reduction $(\Delta \boldsymbol{P})$ at sample time during peak period is estimated in Eq. (19). These generators require to meet the domestic peak demand during peak hours in number of (***N***) houses.

$$\Delta P[MW] = \sum_{i=1}^{N}(P_{BAU} - P_{DSM})_i \quad (19)$$

Where, P_{BAU} is the load induced before DSM program, BAU stands for 'business as usual' and P_{DSM} *is* the load if the control strategies developed are implemented.

Assuming that the DSM program is installed in a sample of (***N***) houses, then, it is required to evaluate the difference in two control cases to determine any energy saving achieved due to the application of the DSM control strategies, shown in Eq. (20) :

$$\Delta E = \sum_{i=1}^{N}(E_{N,BAU} - E_{N,DSM})_i \quad (20)$$

Then the utility avoids initial investment for the peak generator due to the implementation of DSM is estimated in Eq. (21).

$$I_{gen}[\text{US\$}] = \Delta P_{max}[\text{US\$}] \times C_{pp}[\frac{\text{US\$}}{MW}] \quad (21)$$

Where, C_{pp} is the unit cost of the avoided power plant and ΔP_{max} is the maximum load reduction during the peak hours.

Not Purchasing the generator means there is no revenue be had from the sales of electricity. Therefore, it recommended that the utility invests in DSM program to achieve peak reduction; this should be taken into account in the feasibility analysis.

The life cycle costs saving associated with the utility investment is expressed in Eq. (22):

$$LCI_{gen}[US\$] = \left(\sum [\,Variable\ costs\ + fixed\ costs]\ [\frac{US\$}{kWh}]\right) \times E_{gen}[kWh] \tag{22}$$

Where, (***Egen)*** is the electricity generated to meet the energy required in peak hours , fixed costs are associated with insurance, administrative costs, general expenses, depreciation rate and taxes; and variable costs such as fuel and O&M costs.

If the utility installed the DSM program at its own expense for a sample of (***N***) houses then the utility initial investment ($\boldsymbol{I_{DSM}}$) shown in Eq. (23). If the utility also offers the end-users during off-peak hours an off-peak tariff ($\boldsymbol{C_{off-peak}}$) which is less than the peak tariff ($\boldsymbol{C_{peak}}$) , it surely motivates the end-users to implement the DSM program developed. Then the utility life cycle investment ($\boldsymbol{LCI_{DSM}}$) in Eq. (24) shows is the difference in energy selling costs before and after the implementation of the DSM program.

$$I_{DSM} = C_{DSM}\ [US\$/house] \times N\,[house] \tag{23}$$

Where, C_{DSM} is the DSM control unit cost per each participating house (*N*).

$$LCI_{DSM}[US\$] = \left(\Delta E_{peak}[kWh] \times C_{peak}\left[\frac{US\$}{kWh}\right]\right) - \left(\Delta E_{off-peak}[kWh] \times C_{off-peak}\left[\frac{US\$}{kWh}\right]\right) \quad (24)$$

Where, ΔE_{peak} and $\Delta E_{off-peak}$ are the peak and off-peak electrical energy consumption differences before and after the implementation of the DSM program, these values are calculated by use of Eq. (20).

To decide the feasibility of the DSM program the conditions in Eq. (25) has to be satisfied.

$$I_{DSM} < I_{gen}$$
$$LCI_{DSM} < LCI_{gen} \quad (25)$$

7.3.1 Case of North Cyprus

It is noticeable in Figure 4.6 and Figure 7.2 that the peak hours during winter time coincided completely with the second high water consumption period and this causes a high pumping power demand. Unlike the high water consumption during summer time, which is only coincided with a fraction of the summer peak hours. So, it is expected that the pumping controller developed has a higher efficiency in shifting and reducing pumping power demand in winter time compared to summertime.

Considering the house stock of N. Cyprus consists of 242000 houses (Panayiotou, 2010). Assuming that a sample of 10% of these houses which is nearly equal to 25000 houses agreed to implement the pumping controller. The pumping distribution of this sample before and after the implementation of the controller shown in Figure 7.4. This distribution is obtained by iterating the algorithm shown in Figure 7.1 with a randomly water consumption starting time (r) for each house in the sample. The power demand difference of the 25000 houses before and after the controller is the difference between the dashed and the solid power demand in Figure 7.4. Table7.1 lists the pumping electrical energy consumption of the 25000 houses per one day. These values is calculated as the area under the line in Figure 7.4 using Matlab and Eq. (20).

Table7.1: Electrical Energy Consumption after and before the Implementation of the Pumping Controller for a Number of 25000 Houses in Winter Time.

Participating Houses #	Total energy before control during off-peak hours [kWh/day]	Total electric energy consumption without pumping control during peak hours [kWh/day]	Total electric energy consumption with pumping control during off-peak hours [kWh/day]	Total electric energy consumption with pumping control during peak hours [kWh/day]
25000	1148	1480	2653	0

The controller increases the total pumping electrical energy consumption during off-peak hours, such that the electrical energy consumption before the controller is equal to 1148 kWh while after the controller increases to 2653 kWh shown in Table7.1 This is also based on the electrical energy consumption listed in Table7.1 and the assumption variable, and the fixed costs of a diesel backup generator in Table 7.2. The utility life cycle investment, the life cycle avoided costs and the initial investments of the peak generators and of the controller are calculated using Eqs. (21) to Eq. (23).

Table 7.2: Costs of a Diesel Generator (Grunwald, 2015) and (Erciyas, 2014).

Average Fuel Cost	0.15 US$/kWh
O&M	3.75 US$cent/kWh
Insurance, Administrative and General Investment, and other fixed costs	1.5 US$cent/kWh

Assuming that the off-peak tariff is equal to 0.18US$/kWh and the peak tariff is equal to 0.23 US$/kWh. It The utility life cycle avoided costs is equal to 300 US$/day, therefore, it is greater than the utility life cycle investment in the controller which is equal to 69 US$/day.

The pump starting power equals 5 times its steady state power shown in chapter 4. Therefore, assume that the utility purchases a diesel backup generator with a capacity equivalent to the maximum reduced load during peak hours which is equal to 2.85 MW (from Figure 7.4 maximum reduced power is equal to 0.57 MW multiplied by 5) to meet the peak demand. Then the utility initial investment in this generator implementing Eq. (21) with Cpp=710000/MW is equal to 2023500 US$. To avoid this investment the utility can install the controller in the 25000 house with a cost of 1250000 US$ such that the cost of the controller is 50 US$ per each house (float switch, a processor wiring and interface equipment which can be purchased from the market in N. Cyprus at an approximate cost of 10 US$ and 15 US$ installation costs. Assuming that the random pumping is the same during winter time of 150 days in N. Cyprus. The summary of the above analysis shown in Table 7.3 proves that Eq. (25) is satisfied. In other words, it proves that the pumping controller is economically efficient compared to peak diesel generators.

Table 7.3: The Comparison between the Diesel Backup Generator and the Pumping Controller Costs.

Cost item	Backup diesel generator cost (US$)	Second control program costs (US$/day)
Initial investment	2023500	1250000
Life cycle investment during 150 winter days	35000	10350

7.3.2 The Case of Palestine

The details of the Fuzzy controller are introduced in chapter 6 section 6.2. A simulation for a sample of 40 houses was conducted to test the performance of the controller under random operation scenarios of domestic electrical loads. A sample of the results of simulation shown in Figure 7.7. Usually, utility meets power demand by two types of power plants. The first type is to meet the demand below or equal to the base demand.

The second type is to meet the peak demand, these plants are operated just during peak demand.

Assuming that the base demand is equal to 10 amperes equivalent to 88 kW ((10 Amps*40 houses*220 volts)/1000= 88 kW). Any consumption above the base demand is considered a peak demand. The controller always tries to keep the consumption below or equal to this value. Except in some cases, the controller may operate some loads to preserve occupants comfort. For example, the controller may operate the boiler despite the peak demand if the hot water temperature value is not within the range adjusted by the householder (see Figure 7.7 first column house 4).

If the utility decided not to invest in the fuzzy control strategy, then it needs to purchase a diesel backup peak generator to be operated for any consumption above the base demand. Then the capacity of the required generator must be equal to the maximum peak demand between 10-11 AM which is equal to 52 kW (140 kW– 88 kW = 52 kW) (see Figure 7.9). The utility initial investment in the 52 kW generator using Eq. (21) with C*pp*=710000US$/MW (710US$/MW) is equal to 37176 US$.

Figure 7.9 presents the power demand profiles of the 40 houses after and before the implementation of the fuzzy control strategy. The fuzzy controller costs approximately 150 US$ per each house. This cost includes the price of the in-house fuzzy controller (current sensor, a processor wiring and interface equipment which can be purchased from the local market at an approximate cost of 100 US$, and the labor cost is assumed to be 50 USD$). Also, includes each house share of about 5 US$ of the region fuzzy controller price which is equal to 5000 US$ per region. Assuming the utility offered the 40 houses the controller for free, then the utility initial investment in the controller is the cost of the controller of about 6000 US$ (40 houses*150 US$) in addition to 37 kW (124 kW - 88 kW during the period 12:20-1:15 AM) capacity generator with a cost of 26270 US$. Then utility avoided initial investment is equal to 4906 US$ per 40 houses.

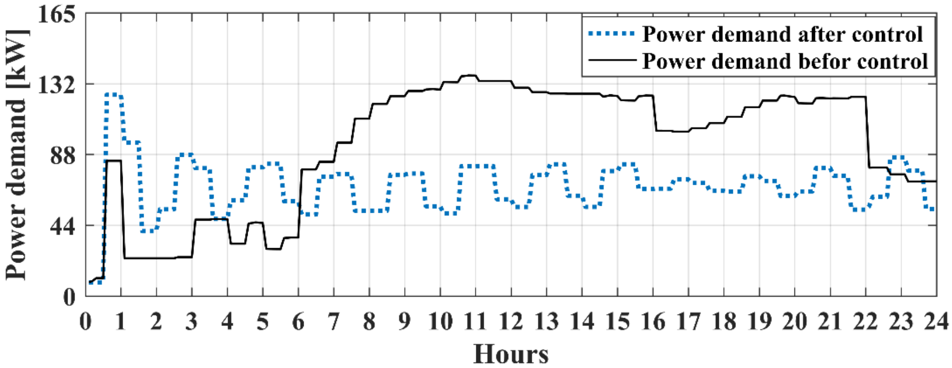


Figure 7.9: Power Demand of 40 houses before and after the Implementation of the Fuzzy Control Strategy (*Note: power was calculated assuming power factor equal 1 power=current*220 volt)*

The controller reduced peak electrical energy consumption of the 40 houses by 63% such that the peak electrical energy consumption before the controller was 1811 kWh/day while after the controller the consumption reduced to 668 kWh/day. Besides, the controller shifted the reduced peak consumption to off-peak hours where the off-peak electrical energy consumption of the 40 houses before the controller was 290 kWh/day while after the controller increases to 961 kWh/day which resulted in flattened power demand profile.

Assuming that the off-peak tariff is equal to 0.18US$/kWh and the peak tariff is equal to 0.23 US$/kWh and using Eq. (24) then the utility life cycle investment is estimated equal to 945 US$/day per each house. The results summary of the above calculations are listed in Table 7.4.

Table 7.4: The Electrical Energy Consumption of 40 Houses before and after Implementing the Fuzzy Control Strategy

	Daily Electrical Energy Consumption (kWh/day)	Peak Electrical Energy Consumption (kWh/day)	Off-peak Electrical Energy Consumption kWh/day
Before fuzzy controller	2253	1811	442
After fuzzy controller	1639	668	971

The summary of the above analysis in Table 7.5 proves that Eq. (25) is satisfied. In other words, it proves that the investment in fuzzy controller is economically efficient compared to peak diesel generators.

Table 7.5: The Comparison between the Diesel Backup Generator the Fuzzy Control Strategy Costs

Cost item	Backup Diesel Generator Cost (US$)	Fuzzy Control Strategy Costs (US$)
Initial Investment	37176	32270
Life cycle investment a day	417	199

7.4 Environmental Impact

The proposed peak load reduction strategies in this research decreases the need for peak backup generators. In other words, the strategies decrease the energy production from conventional powered petrol or solid fuels generators. The combustion of these fuels emits greenhouse gas such as CO_2 and this causes serious environmental damage . These strategies could assist the utilities foresee the optimal schedule that operates the base and peak generators efficiently. The optimal scheduling reduces the frequency of “Startups” and “Shutdowns” of the generators, as a consequence, this is reduces the gas emissions (Abaravicius et al., 2006). The maintenance requirement of the generators is also reduced due to the implementation of the load reduction strategies, accordingly, the disposable metals and oils which harms the environment are reduced.

7.5 Chapter Summary

The chapter addresses the environmental, the electrical, and economic impacts of the control developed strategies . It testifies that the investment in these strategies is more economically efficient compared to the conventional peak generators. Besides, control strategies developed are reliable, simple to use andacquire.. The most significant aspect about the controllers developed that they are environmentally friendly; they reduce CO_2 gas emission and the use of fossil fuel powered-generators.

Chapter 8

CONCLUSION AND FUTURE WORK

8.1 Concluding Remarks and Lessons Learned

The ultimate goal of the domestic peak load reduction strategies developed is to reduce domestic peak demand and at the same time preserve the electric usage comfort of the consumer. From the present research, the following conclusions can be drawn:

- It is possible to design control units, which work without needing a smart grid, in developing nations experiencing capacity problems during peak hours.
- Contrary to previously developed DR programs, in the present control approaches there is no interference by the utilities or end-users during the operation of any devices. The switching on/off of all devices takes place automatically. The operation can be said to be standalone.
- The control strategies developed can be integrated within modern home control technologies, therefore they can be implemented in countries where conventional grids are still in use. In other words, this integration provides the capability to measure and monitor the variables needed to accomplish their work.
- The technologies required to build these control units are available in the markets of these nations. In addition, these control units can easily be handled and implemented by electrical technicians.
- The controllers are flexible, such that their structure, design and control variables can be modified to interact with any change in the controlled

environment. Therefore, they can be applied in other sectors such as the commercial and hotel sectors.

8.2 Conclusion

8.2.1 Pumping Work Control Strategy

A simple, practical, computational and cost-effective shifting water level control algorithm manages the water-energy nexus by reducing pump-storage system electrical energy consumption during peak hours. The proposed algorithm requires a simple modification to the existing water level control scheme, by installing an additional float switch in the rooftop water tank below the currently available float switch which is usually adjusted to trigger the pump when the level in the tank drops by 5-10% from its maximum. Based on the simulation results, the algorithm preserves domestic end-users' comfortable daily water demand and reduces water pump energy consumption during peak hours by 90%. During off-peak hours, the control algorithm triggers the pump to refill the rooftop tank based on the upper float switch when water level drops by 5%. During peak hours, the pump is triggered only when the water drops by 30%. The performance of the algorithm is found to be comparable to the performance of the model predictive control (MPC) approach developed for the same purpose, but MPC needs high computational capacity and a complex analogue feedback level sensor. The algorithm succeeds in reducing and shifting pump energy consumption under various possible operational scenarios and water demand disturbances. A mathematical model is developed for the domestic water pump-storage system using Matlab/Simscape to cope with the complexity of solving nonlinear fluid flow equations and measure the data required to develop the control algorithm. The performance of the algorithm is tested based on the conditions of N. Cyprus as real case study.

8.2.2 Fuzzy Logic Control Strategy

A power management technique utilizing an intelligent closed-loop fuzzy control approach has been developed for residential buildings particularly applicable in developing countries where conventional grids are still used, to reduce the possibility of blackouts arising from electricity shortages during peak hours. Two fuzzy controllers have been designed to shift the operating times of water pumps, electric water heaters, refrigerators, lighting systems, dishwashers and clothes washing machines to off-peak times without affecting consumer comfort. First, an in-house fuzzy controller controls each load using a set of prescribed rules, such that the peak current for overall consumption of any home is not exceeded. Second, a regional fuzzy controller monitors the overall current consumption of the region and controls the operation of the in-house fuzzy controllers to prevent loads throughout the region being shifted to the same time, which may cause a regional current consumption overload. The Matlab/Simscape toolbox compares the current profiles of various operational scenarios before and after the controllers are applied. Several operational scenarios are tested to ensure the controller avoids certain current peaks. The control strategy reduces the peak electric energy consumption by 63% as well as shifting the reduced consumption to off-peak times, resulting in a smoother power demand profile. The principle of cooling and electric energy storage during off-peak times is utilized in managing the operation time of boilers and refrigerators.

An experimentally validated power consumption model, following the bottom-up modelling approach developed in Palestine, tests the performance of the fuzzy controllers. A detailed case study in which power demand is observed over five consecutive days has been undertaken to verify the suggested model, from which an average error of 8.44% of model output, relative to actual power demand, results. The factors affecting the power demand have been investigated, including socio-demographic factors and the availability of house occupants. The model can be used for residential renewable energy systems, and for applying demand-side management programs. Moreover, the model can help designated authorities with strategic planning of future power demand.

8.3 Research Limitations

The following points are the potential limitations of this research:

- A sample of houses is considered to measure the domestic power demand profiles, combined with a questionnaire to determine the effect of socio-demographic factors on power demand. The size of this sample is small, partly because the occupants considered these measurements and questions to be private information.
- The control strategies developed are limited to managing the operation time of six domestic electric loads. The common factor of these loads is that they can be shifted to off-peak hours without disturbing the comfort of end-users. If more loads were considered the control strategies would need to be more efficient in reshaping domestic power demand profiles.
- The robustness of the fuzzy control strategy is sensitive to the quality and availability of communication infrastructure, such that the strategy management work depends on real-time data exchange between the regional controller and the in-house controllers.
- The fuzzy control strategy is limited to regions with mains distribution electrical grid lines with voltage capacity of 400 Vac and domestic distribution

lines of 220Vac. In other words, the regional controller must be positioned near the region's main circuit breaker.

- The occupants' comfort level is assigned as a high level priority constraint to the operation of the strategies. Another assigned constraint is that the controllers do not interrupt the operation of mode-operation appliances if they are already running. These constraints inhibit the controllers work despite peak demand.

8.4 Future Work

The following are future potential research topics:

- Throughout the design of the fuzzy logic controllers, a signal from each load could inform the controller about the instantaneous state of the load. This requires costly technology such as KNX input switches. These switches can be replaced by just one current sensor which measures the total house current profile, then, by applying pattern recognition algorithms, information about the statuses of the loads can be estimated from the total consumed current profile.
- Developing a mathematically well defined load control strategy is a complicated process because of the non-deterministic variables that affect the domestic power demand. Therefore, it is recommended to interface machine learning control strategies due to their flexibility in including such variables.
- In developing nations, the integration of renewable energy sources for domestic use is a helpful solution to reducing dependency on conventional electric grid resources.
- A database of the actual power demand profiles of domestic electric loads would be a very helpful tool in the modelling of domestic power consumption.

- One can find barely an energy models for developing countries, therefore, such energy models are needed for the planning of load management programs and strategic planning of future energy demand in these countries.
- The uncertain synchronization between the measured data inputs and the output decisions in real-time may lower the performance efficiency of the controllers. Therefore, the input data can be replaced by a short term forecasting model to be built based on historical daily or weekly measurements.
- The impact of the controllers developed on the electric grid, such as imbalance, voltage drop limits, flow capacity limits and diversity and load factors, should be investigated.
- The power consumption model developed can be further improved by considering start-up currents when modelling electrical devices, or by accurately modelling thermal devices, including refrigerators and HVACs, with internal control programs.

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APPENDICES

Appendix A: Measurement of Power Consumption Profiles

1. House 4

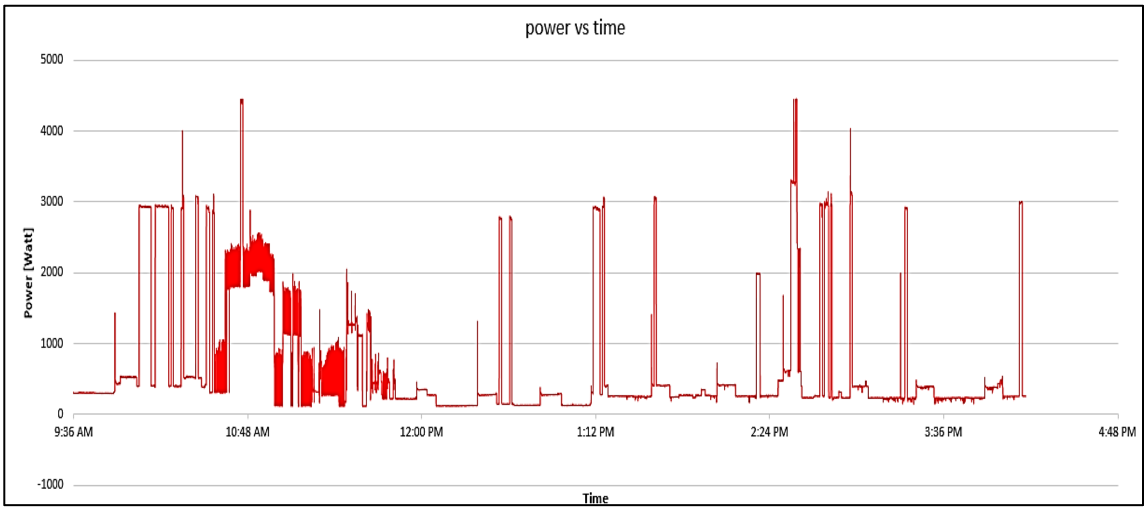


Figure 1: Electricity consumption of the home 4 from 9 am to 5 pm.

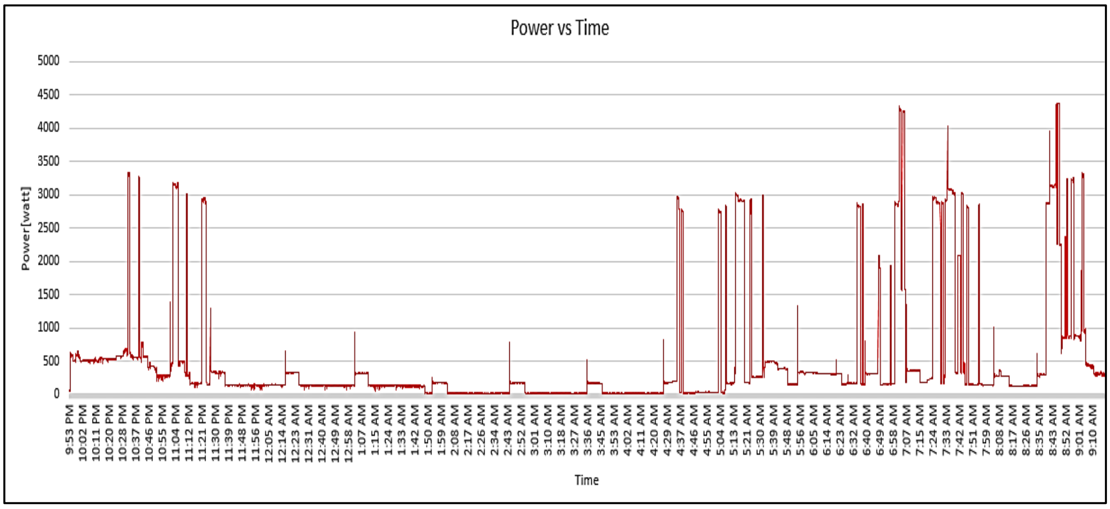


Figure 2: Electricity consumption of the home 4 from 9 pm to 9 am.

2. House 5

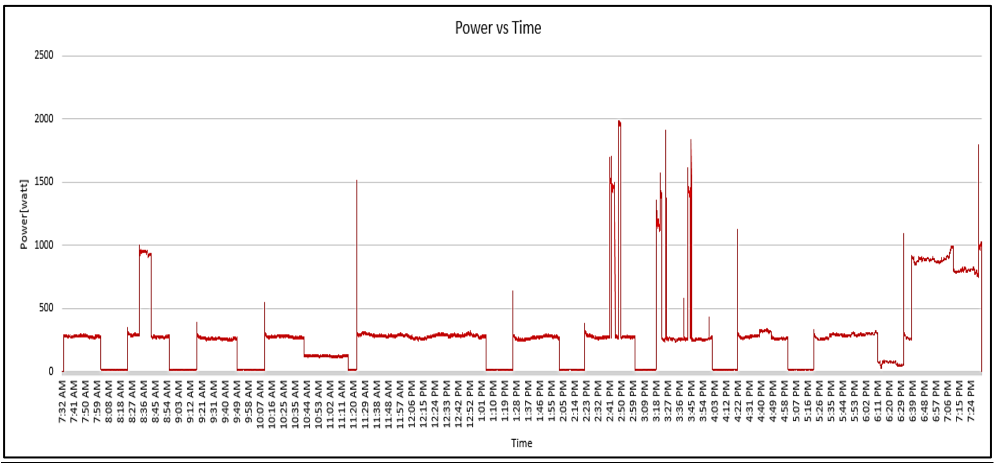


Figure 3: Electricity consumption of the home 5 from 7 am to7 pm.

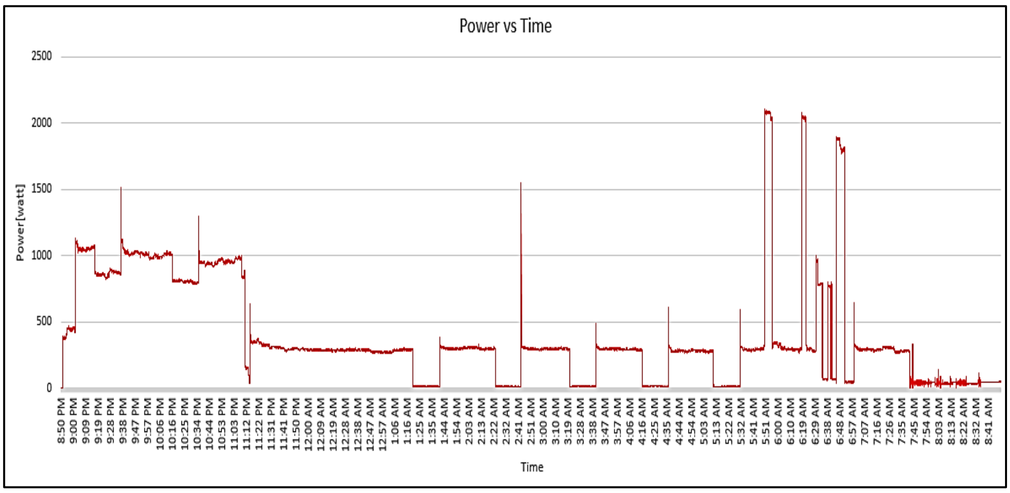


Figure 4: Electricity consumption of the home 5 from 8 pm to 8 am.

3. House 6

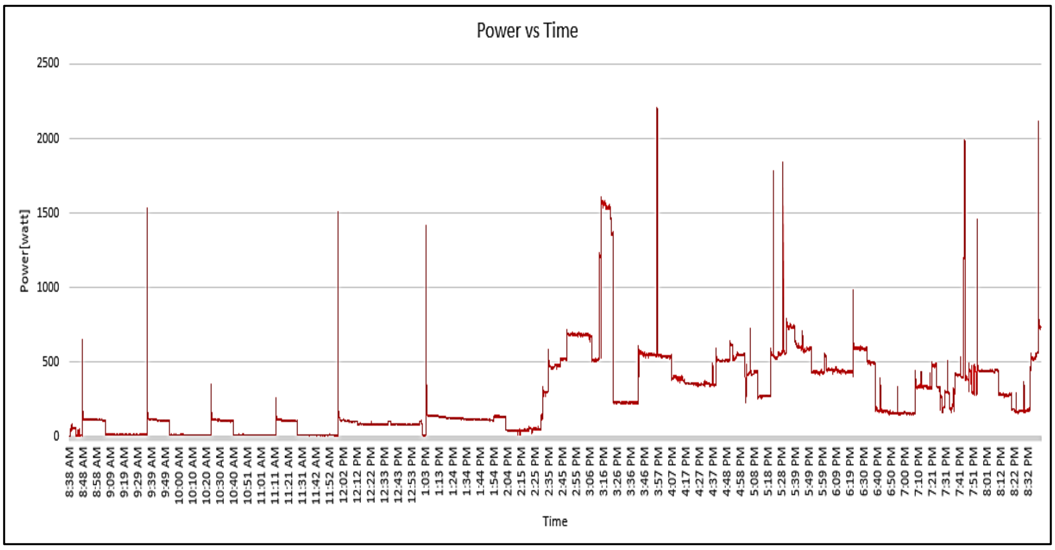


Figure 5: Electricity consumption of the home 6 from 9 am to9 pm.

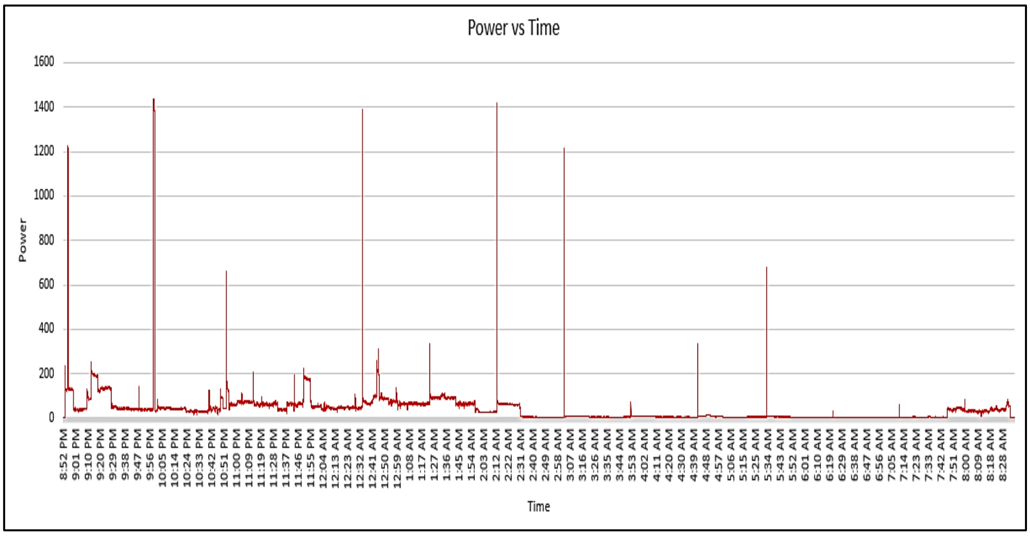


Figure 6: Electricity consumption of the home 6 from 9 pm to 9 am.

4. House 7

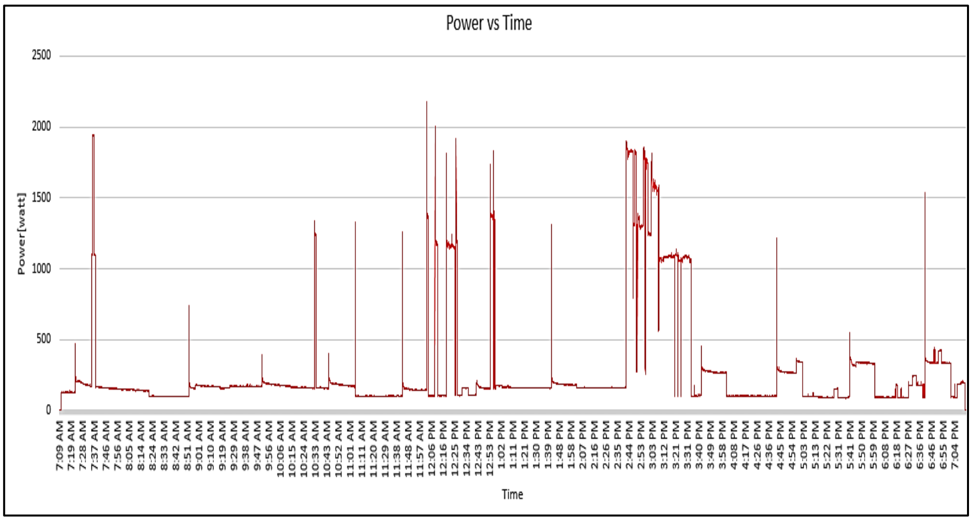


Figure 7: Electricity consumption of the home 7 from 7 am to 7 pm.

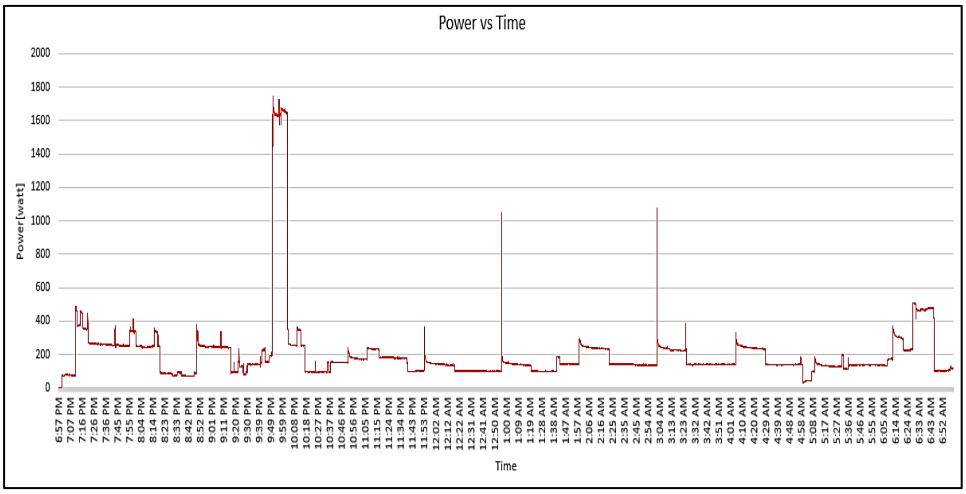


Figure 8: Electricity consumption of the home 7 from 7 pm to 7 am.

5. House 8

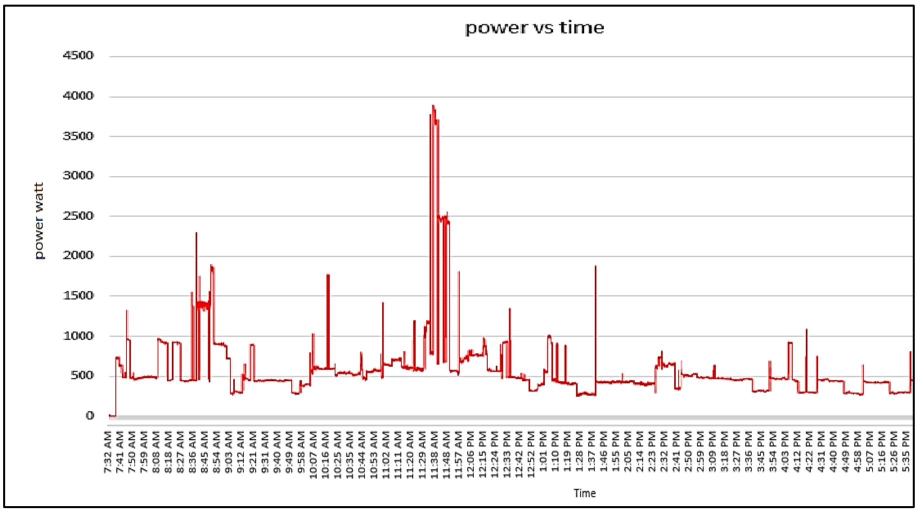


Figure 9: Electricity consumption of the home 8 from 7 am to 6 pm.

6. House 9

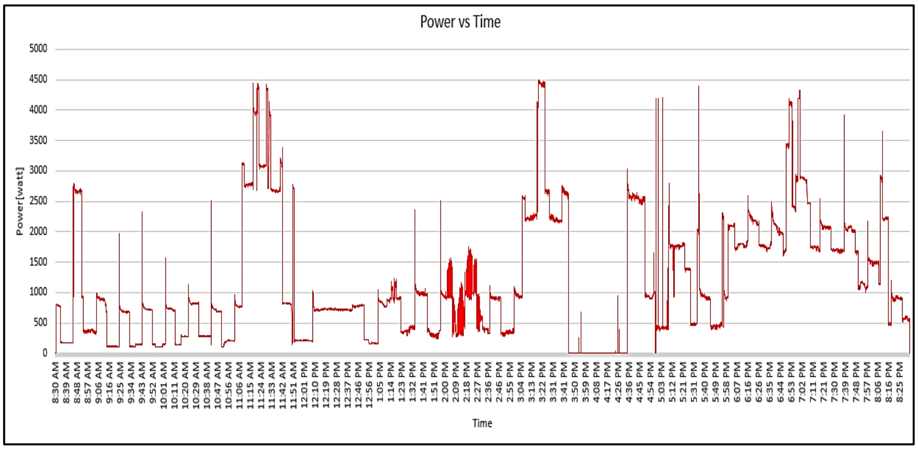


Figure 10: Electricity consumption of the house 9 from 8:30 am to 8:30 pm.

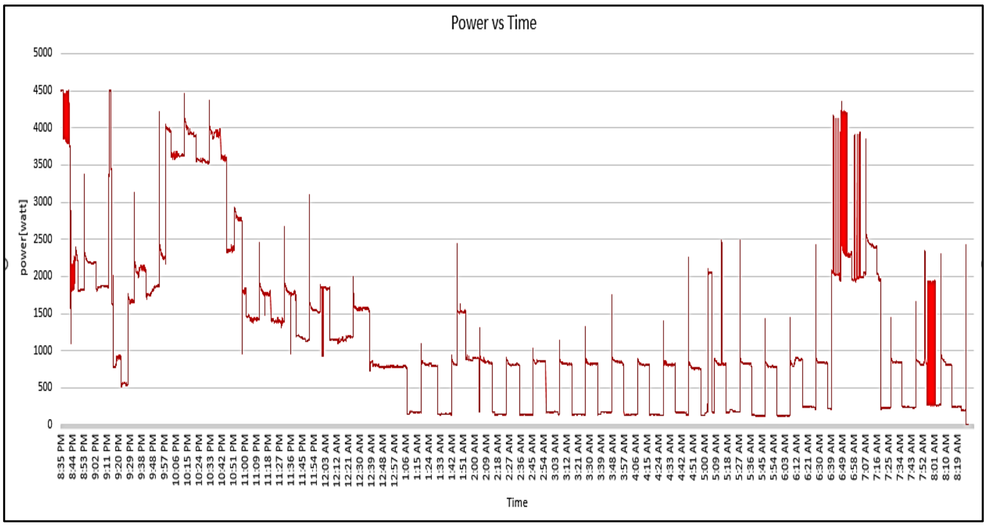


Figure 11: Electricity consumption of the house 9 from 9 pm to 9 am.

7. House 10

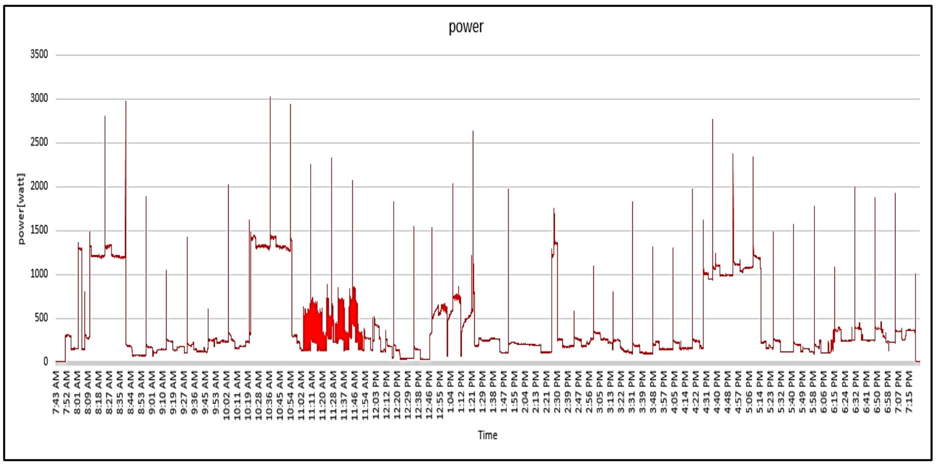


Figure 12: Electricity consumption of the home 10 from 7:45 am to 7:15 pm.

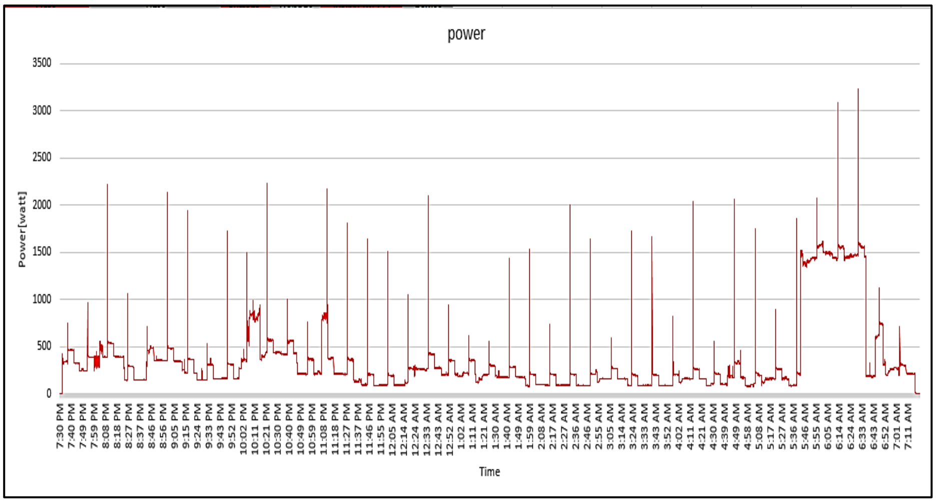


Figure 13: Electricity consumption of the home 10 from 7:30 pm to 7:15 am.

Appendix B: Questionnaire

Objective: To study the electrical energy consumption in Hebron house stock. Please answer all the questions and the information provided will be used just for the purposes of scientific research**.**

1. Address: ………………………………………………………………………………………

2. Number of Family members: ………….

   School students: ………....

   University students: …………

3. Educational level of the householder: ☐ Universal. ☐ Low than universal.

4. Householder wife job: ………………………………………………

5. Family incomes level monthly: ☐ 800 US$ or less. ☐ 800 _ 1600 US$. ☐ 1600 US$ or more.

6. Nature housing: ☐ Own. ☐ Rent.

7. Home area: …………... m^2.

8. No. of rooms: …………

9. Committed to pay electricity bill: ☐ Monthly. ☐ Many months. ☐ Not committed.

10. How do you see the consumption of electricity in your home?

    ☐ Low. ☐ Normal. ☐ High. ☐ Very high.

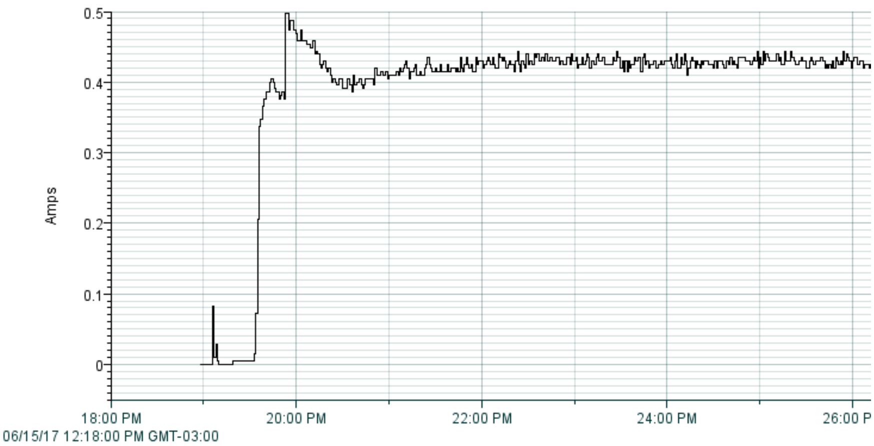
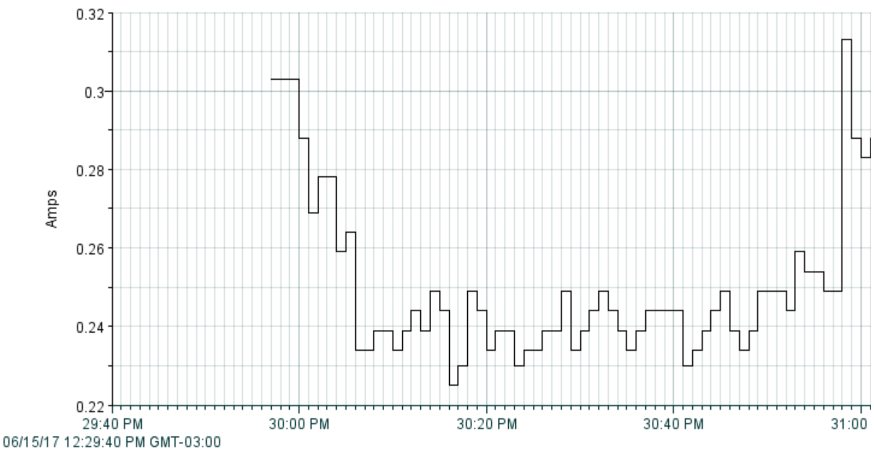
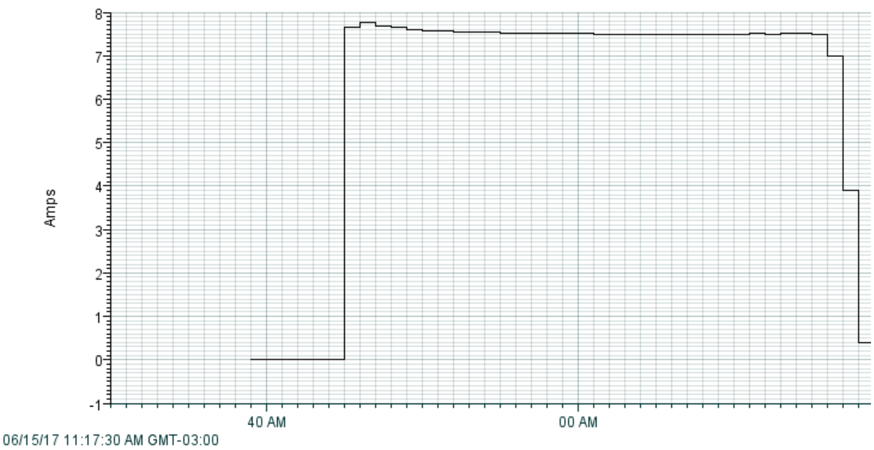
11. Do you save electricity in your home?

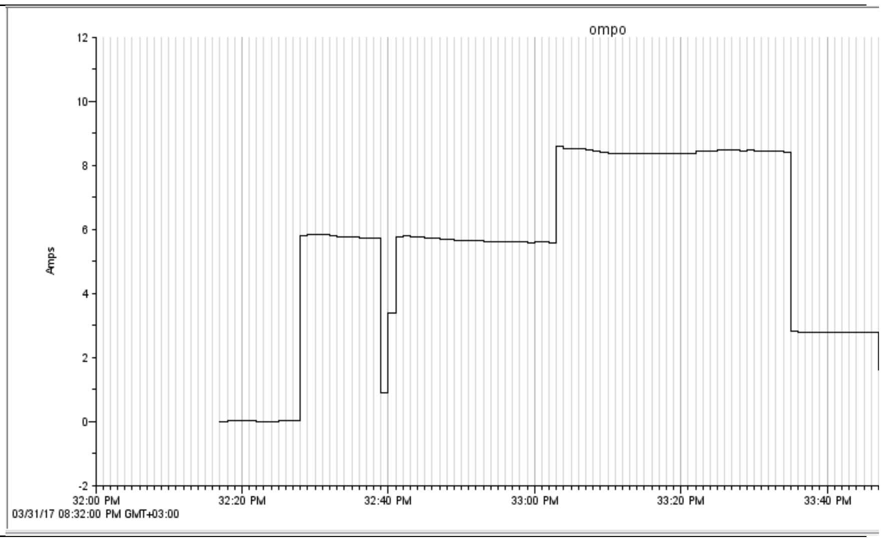
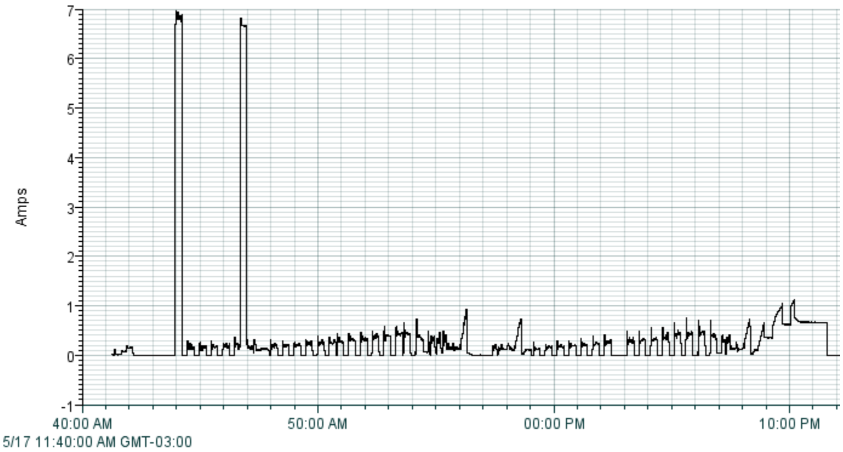
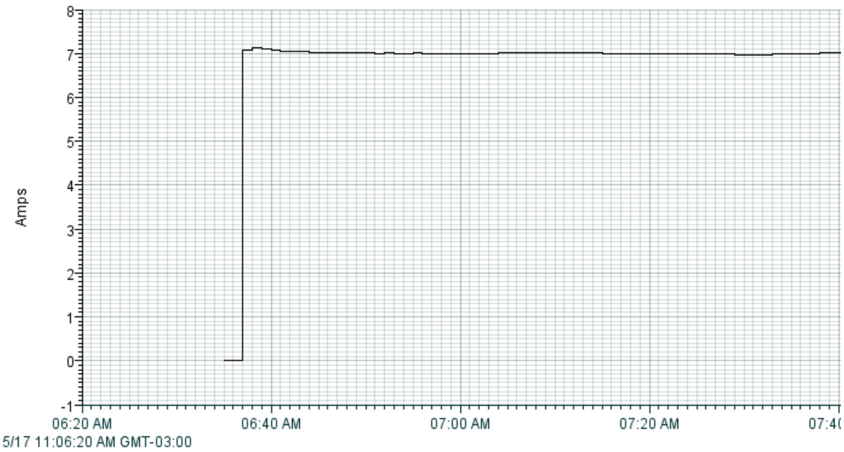
    ☐ Sometimes. ☐ Yes. ☐ No.

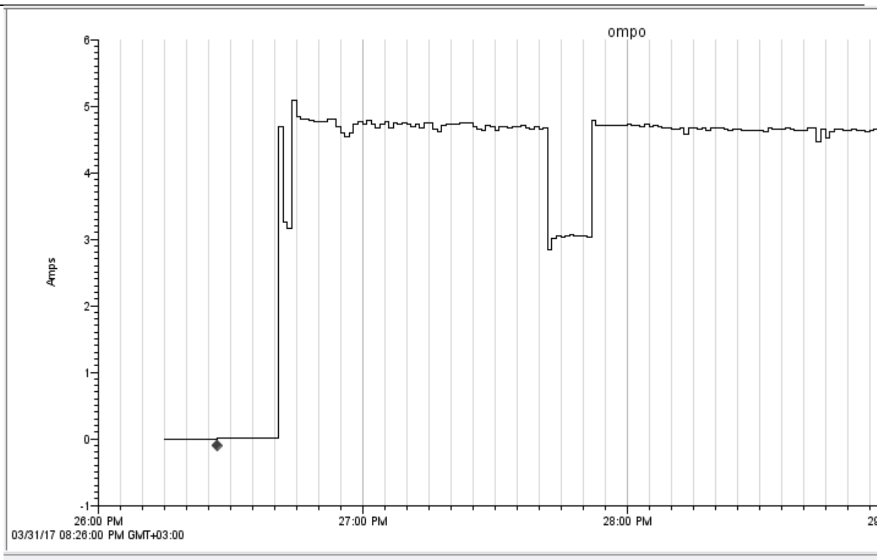
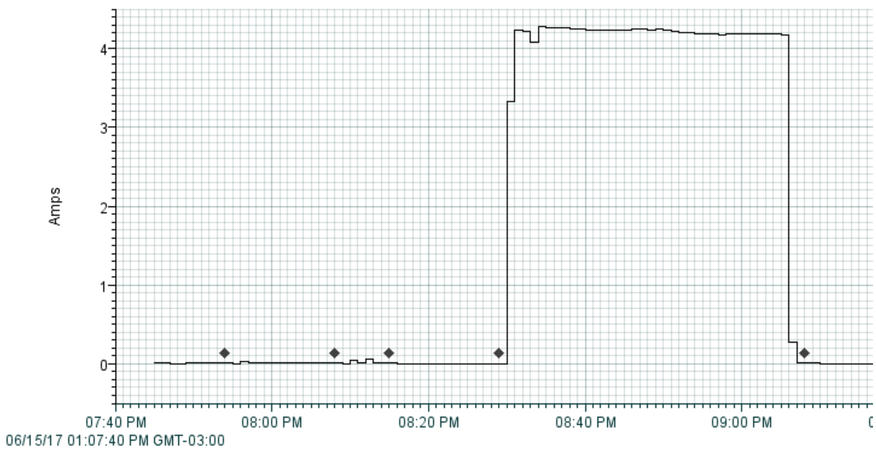
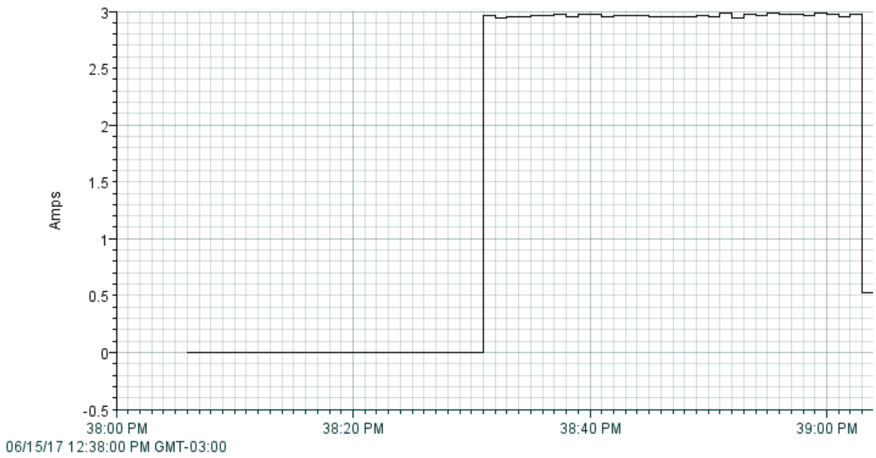
Devices in your home:

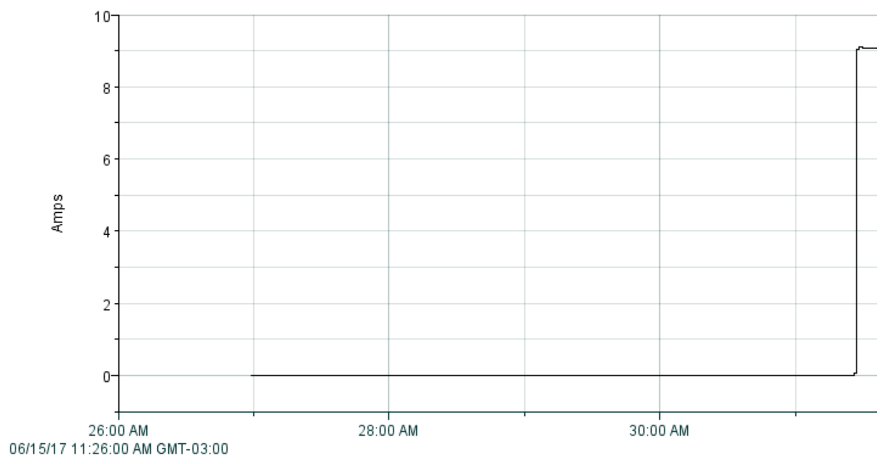
No.	Device	Exist	Doesn’t exist	Rating Watts	Operation Hours
1	Washing Machine				
2	Hair Dryer				
3	Microwave				
4	Toaster				
5	Clothes Dryer				
6	Electric furnace				
7	Water pump				
8	Boiler				
9	Water Heater				
10	Air conditioner				
11	Vacuum Cleaner				
12	Electric Fireplace				
13	Dishwasher				

Appendix C: Typical House Electric Loads Power Ratings and Their Actual Current Profiles

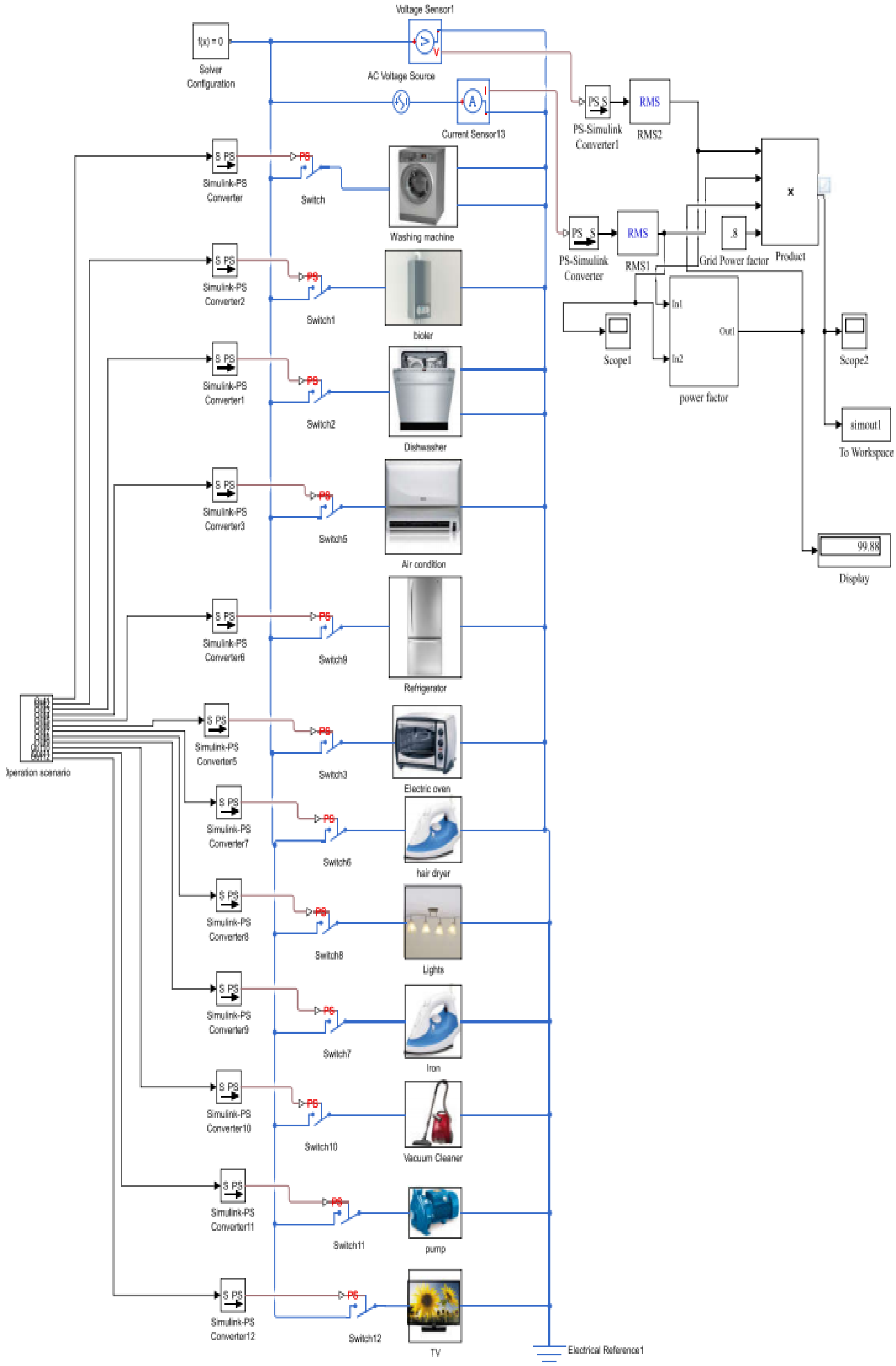
Device	Current Profile
Refrigerator Manufacture company: LG, rated power 160 W Load design nature: **Inductive**	
TV and receiver Manufacture: LG, rated power 200 W Load design nature: **Capacitive**	
Hair dryer Manufacture company: Super Solano, rated power 2000 W. Load design nature: **Resistive**	

Electric house heater used in Kitchen Manufacture company: Mega, rated power 2400 W. Load design nature: **Resistive**	
Washing machine Manufacture company: LG, rated power 1800 W. Load design nature: **Resistive+Inductive**	
Water electric boiler Manufacture company: Mienta, rated power 2000 W Load design nature: **Resistive**	

Vacuum cleaner Manufacture company: Hommer, rated power 1200 W. Load design nature: **Inductive**	
Iron Manufacture company: Ariete, rated power 1900 W. Load design nature: **Resistive**	
Electric Pump ¾ hp Italy made Load design nature: **Inductive**	

Electric Oven Manufacture company: Universal 2400 watt Load design nature: **Resistive**	

Appendix D: Electric Energy Model



Appendix E: Data Sheets

onset

HOBO® Data Loggers

HOBO® U12 Logger

Multi-channel energy & environmental monitoring

HOBO U12 data loggers provide flexibility for monitoring up to 4 channels of energy and environmental data with a single, compact logger. They provide 12-bit resolution measurements for detecting greater variability in recorded data, direct USB connectivity for convenient, fast data offload, and a 43K measurement capacity.

Supported Measurements: Temperature, Relative Humidity, Dew Point, 4-20mA, AC Current, AC Voltage, Air Velocity, Carbon Dioxide, Compressed Air Flow, DC Current, DC Voltage, Gauge Pressure, Kilowatts, Light Intensity, Volatile Organic Compound (some sensors sold separately)

Key Advantages:

- Records up to 4 channels
- Your choice of three models, with flexible measurement options
- Programmable as well as push-button start
- Compatible with a broad range of external sensors

Minimum System Requirements:

Software USB cable*

Split-core AC Current Transformer (CTV-x)
(AC Amperage to DC Voltage Transducer)

For use with HOBO® U12 and UX120-06M data loggers and HOBO ZW data nodes

Specifications

Current Range	CTV-A 2-20 AMPS AC CTV-B 5-50 AMPS AC CTV-C 10-100 AMPS AC CTV-D 20-200 AMPS AC CTV-E 60-600 AMPS AC
Accuracy with U12	±4.5% of full scale (includes logger accuracy)
Accuracy with ZW	±4.0% of full scale (includes data node accuracy)
Accuracy with UX120-006M	±2.1% of full scale (includes logger accuracy)
Response time (from 10% to 90% of amplitude):	CTV-A approx. 440 milliseconds CTV-B approx. 200 milliseconds CTV-C approx. 100 milliseconds CTV-D approx. 450 milliseconds CTV-E approx. 490 milliseconds
Input Current	AC current, sine wave, single phase 50 Hz or 60 Hz, load power factor 0.5 to 1.0 lead or lag
Output	0-2.5 V DC
Voltage rating	600 V AC
Temperature rating	CTV-A, CTV-B, CTV-C: -15° to 60°C (5° to 140°F), CTV-D, CTV-E: -15° to 40°C (5° to 104°F)
Construction	Molded plastic housing for indoor use per UL508
Cable	1.8 m (6 ft.)
Window Size	CTV-A, CTV-B, CTV-C: 28 x 20 mm (1.1 x 0.8 in.) CTV-D: 39 x 32 mm (1.54 x 1.26 in.) CTV-E: 74 x 62 mm (2.92 x 2.46 in.)
Dimensions	CTV-A, CTV-B, CTV-C: 79 x 71 x 36 mm (3.1 x 2.8 x 1.4 in.) CTV-D: 100 x 120 x 29 mm (3.92 x 4.72 x 1.14 in) CTV-E: 135 x 150 x 28 mm (5.3 in. x 5.91 in. x 1.12 in.)
CE	The CE Marking identifies this product as complying with all relevant directives in the European Union (EU)

Part number	U12-006 (4 Ext)	U12-012 (Temp/RH/Light/Ext)	U12-013 (Temp/RH/2 Ext)
Memory	43,000 measurements		
Sampling rate	1 second to 18 hours, user-selectable		
Battery life	1 year typical, user-replaceable, CR2032		
		Temperature	
Max range		-20° to 70°C (-4° to 158°F)	
Accuracy		± 0.35°C from 0° to 50°C (± 0.63°F from 32° to 122°F)	
Resolution (12-bit)		0.03°C @ 25°C (0.05°F @ 77°F)	
		Relative Humidity	
Measurement range		5% to 95% RH (non-condensing)	
Accuracy		± 2.5% typical, 3.5% maximum, from 10 to 90% RH	
Resolution (10-bit)		0.03% RH	
		Light Intensity	
		Designed for general purpose indoor measurement of relative light levels	
Range		1 to 3000 footcandles (lumens/ft2) typical 0-32,300 lumens/m2	
	External Input		
Range	0 to 2.5 VDC		
Accuracy	± 2 mV, ± 2.5% of absolute reading		
Resolution	0.6 mV		
CE compliant	Yes		

Potential Voltage Transformers SPT-0375

Provides Proportional Voltage For 115 To 460 Volt AC

Description:

The Magnelab SPT-0375 series of potential transformer provides a linear output voltage proportional to the input voltage. The output voltage is ANSI standard of 0.333 volt making the SPT series ideal for data loggers and other electronic measuring instrumentation. Custom outputs and other parameters are available at customer request.

Features:

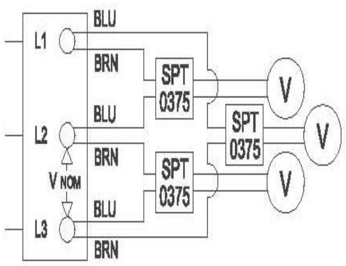
- Rated input from 115 volts to 460 Volts
- Output of 0.333 Volt at rated voltage
- Linearity accuracy ± 1%
- Accuracy at 10% to 130% of rated voltage
- Phase angle < 1 degree
- Withstand voltage of 2,500 Vrms primary to secondary
- Input leads 14 AWG 8 ft., Output leads 22 AWG 8 ft.
- Two mounting holes using #8/32 blind inserts
- UL Recognized, CE, RoHS Compliant

PART NUMBER AND RATING	
SPT-0375-150	Rated 115 VAC
SPT-0375-300	Rated 230 VAC
SPT-0375-600	Rated 460 VAC

DIMENSION	INCH	MM
A	1.350	34.29
B	1.750	44.45
H	1.470	37.34
L	2.230	56.64
W	1.830	46.48

Possible 3 Phase Connections:

Delta



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