OPTIMAL MANAGEMENT OF HOUSEHOLD LOAD UNDER DEMAND RESPONSE

by

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SUMMARY

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Keywords:	demand side management, demand response, household energy management, scheduling, mixed integer nonlinear programming (MINLP), battery energy storage system, photovoltaic,carbon emissions, time-of-use, economic analysis.

Residential demand response (RDR) is one of the demand side management (DSM) programs for smart grid applications that are designed to enable utility companies to manage the user-side electrical loads and also for consumers to voluntarily lower their demand. Instead of adding more generators to the electrical power system, RDR programs pay residential energy users to reduce consumption. Due to the complex interactions between residential customers and the power utility companies; in this thesis, RDR is studied using an optimization approach for the reason that optimization of energy consumption, with consequent cost reduction, is among the primary problems of the present and future smart grid. In this thesis optimal control models are formulated to study household energy management under time-of-use (TOU) electricity pricing strategy.

The initial optimal control mathematical model is developed where consumers attempt to find the best way to schedule their household electrical resources depending on the tariff provided by the utility and the incentive offered during peak times. Under such a setting, whenever customers have enough transferable appliances, significant energy cost savings can be achieved with proper modelling of appliance usage in a household. Consumer behaviour

plays a crucial role in ensuring that RDR is achieved. It has been discovered in this thesis that; inconvenience, incentive, budget and coordination of appliances affect consumer's energy consumption behaviour. Other areas that need attention in order to further enhance the solutions of the research question are investigated. It has been shown that by incorporating the storage and photovoltaic (PV) generator the consumer can increase cost savings and reduce their electricity peak consumption further as well as the total energy drawn from the grid. Insights on the complexity of the optimization problem are provided, to allow customers to better determine the trade-off between complexity, cost, and the need to schedule their energy resources. The derived models provide a blueprint for integrating demand-side management and scheduling of resources.

The other part of the study proposes an optimal energy management system that combines DSM strategies for aggregated households; DR with a dedicated PV and battery which shows that the aggregated consumption can reduce the power demanded from a distribution system by a significant amount and thus relieve the power system network and afford some residential members significant collective savings. Further more, it is shown in this thesis that knowledge on carbon emissions can incentivize investment in renewable energy at household level. It is also demonstrated that the consumer's preferences on the cost sub-functions of energy, inconvenience and carbon emissions affect the consumption pattern. These results are important for both the consumer and the electricity suppliers, as they illustrate the optimal decisions considered in the presence of multiple sub-objectives.

In this work, field measurements are carried out to obtain the baseline appliance commitment and these are compared with the optimal solutions obtained through the inconvenience model.

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OPSOMMING

DIE OPTIMALE BESTUUR VAN HUISHOUDELIKE ELEKTRIESE LAS GEDURENDE AANVRAAGKANTREAKSIE

deur

Ditiro Setlhaolo

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Departement:	Elektriese, Elektroniese en Rekenaar-Ingenieurswese
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Graad:	Philosophiae Doctor (Elektriese Ingenieurswese)
Sleutelwoorde:	aanvraagkantbestuur, aanvraagkantreaksie, huishoudelike bestuur van energie, skedulering, nie-lineêre programmering van gemengde heelgetalle, battery-energie-opgaarstelsel, fotovoltaïese, oplossing van beperkte heelgetalprobleme, tyd van gebruik, ongerief.

Huishoudelike vraagrespons (HVR) is een van die vraagkantbestuur- (VKB) programme vir slimnetwerktoepassings wat ontwerp is om elektrisiteitsmaatskappye toe te laat om verbruikerskant- elektriese las te bestuur, asook om verbruikers toe te laat om hul elektriese aanvraag vrywillig te verlaag. In plaas daarvan om meer elektrisiteit te genereer, betaal HRV-programme huishoudelike verbruikers om hul verbruik te verlaag. Daar is komplekse interaksies tussen huishoudelike verbruikers en die elektrisiteitsmaatskappye. Daarom is die tesis dat HVR, benader vanuit 'n optimeringsperspektief, met gevolglike kostebesparing, een van die hoofuitdagings van die toekomstige slimnetwerk is. In hierdie tesis word optimale beheermodelle geformuleer om huishoudelike energiebestuur onder die tyd-van-verbruik- (TVV) prysstrategie te bestuur.

Die aanvanklike optimale beheer wiskundige model word ontwikkel sodat die verbruiker sy elektrisiteitsverbruik skeduleer om gebruik te maak van die aansporing wat tydens spitstye gebied word. Sodoende kan noemenswaardige energiekostebesparings word, as verbruikers oor genoeg verskuifbare elektriese toestel-laste beskik. Verbruikersgedrag speel 'n deurslaggewende rol om HVR te verseker. Daar is in hierdie tesis bepaal dat ongerief, aanspor-

ing, begroting, en koördinasie van toestelle verbruikers se energieverbruikgedrag beïnvloed. Ander areas wat aandag nodig het ten einde oplossings te verbeter, word ook ondersoek. Daar word getoon dat deur energiestoring en fotovoltaïese (FV) generators te gebruik, die verbruiker sy kostebesparings kan vergroot en sy spitstydelektrisiteitsverbruik verder kan verlaag. Insigte in die ingewikkeldheid van die optimeringsprobleem word verskaf, ten einde verbruikers te help om kompleksiteit, koste en die skedulering van energiehulpbronne te bestuur. Die modelle verskaf 'n bloudruk vir geïntegreerde VBK- en toestelvlakskedulering.

Die volgende gedeelte van die studie stel 'n optimale energiebestuursisteem vir VBK-strategieë met gesommeerde huishoudings voor. VR met 'n toegewyde FV-sel en battery word gebruik, en daar is bevind dat die gesommeerde verbruik noemenswaardig verminder kan word. Dit bring noemenswaardige gesommeerde besparings vir sekere huishoudings teweeg, en verminder ook die las op die elektrisiteitsnetwerk. Die volgende gedeelte van die studie wys dat kennis van koolstofvrystellings beleggings in hernubare energie kan aanspoor op huishoudelike vlak. Daar word ook bewys dat verbruikersvoorkeure met betrekking tot energie, gerief, en koolstofvrystellings verbruikpatrone affekteer. Die resultate is belangrik vir beide elektrisiteitsverskaffers en vebruikers, en illustreer optimale besluite gegewe die kompromieë tussen teenstrydige doeleindes.

In hierdie werk word veldmetings gebruik om basislyntoesteltoewydings te bepaal en te vergelyk met optimale oplossings wat deur simulasie verkry is.

ACKNOWLEDGEMENT

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TABLE OF CONTENTS

LIST OF ABBREVIATIONS

AC	Alternating current
AMI	Advanced metering infrastructure
BESS	Battery energy storage system
CMP	Capacity market program
CO_2	Carbon dioxide
CPP	Critical peak pricing
DB	Distribution board
DC	Direct current
DLC	Direct load control
DOD	Depth of discharge
DR	Demand response
DSM	Demand side management
EEC	Energy efficiency and conservation
ED-CPP	Extreme day critical peak pricing
EDP	Extreme day pricing
EDRP	Emergency demand response program
EWH	Electric water heater
HAN	Home area network
I/C	Interruptible/Curtailable service
ISO	Independent system operator
MILP	Mixed integer linear programming
MINLP	Mixed integer nonlinear programming
PHEV	Plug-in hybrid electric vehicle
PV	Photovoltaic generator
RDR	Residential demand response
RLM	Residential load management
RTO	Regional transmission organizations
RTP	Real time pricing
SCIP	Solving constraint integer programs
SOC	State of charge
TOU	Time-of-use

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 PROBLEM STATEMENT AND MOTIVATION

Balancing electrical energy supply and demand in a power system in real time has always been a global practical challenge with the energy safety gap being below anticipated margins. The major contributors of these challenges are the ever-mounting electricity demand due to massive global urbanisation and aging infrastructure[1,2] [1, 2]. During this type of situation, interruptions are inevitable and consumers of all types are expected to take part in reducing consumption. Traditionally utilities commit conventional peaking power plants in order to increase the power generated to meet the rising demand[3]. The challenges with peaking plants have been attributed to economic and environmental problems [3–5]. The other challenge that the global electricity sector is facing is the fight against climate change[4]. Because of these challenges the world is moving towards new innovative methods where consumers have to alter their energy consumption to the available generated power in order to reduce their electricity costs and to maintain the reliability of the electrical grid [6]. Smart grid, as a new promising technology that can mitigate these problems is currently being developed by utilities to revolutionize the existing electrical grid by allowing two-way communications to enhance the economics, reliability, efficiency and sustainability of the generation, trans-

[1] M. Clark, Aging US power grid blacks out more than any other developed nation, 17 July 2014. <http://www.ibtimes.com/>.

[2] International Energy Agency IEA, Tackling investment challenges in power generation, 2007.< https://www.iea.org/publications/freepublications/publication/tacklinginvestment.pdf>

[3] Enernoc, What is demand-side management?.<http://www.enernoc.com/our-resources/term-pages/what-is-demand-side-management>

[4] COP17/CMP7, United Nations, Conference on climate change, 28-9 Dec. 2011, Durban, South Africa.< http://www.cop17-cmp7durban.com>

mission, distribution and utilization of electrical power [1, 7–9]. However, to achieve the full benefits of smart grid, associated complex challenges such as; technological and policy issues must be addressed first [7, 10–12].

Demand-side management (DSM) techniques are becoming a major step in the realization of the smart grid systems. DSM are programs that have been shown over the years to contribute to electrical energy reduction by commercial, industrial and residential consumers. Globally, power utilities are gradually moving towards employing tools and programs that enable DSM programs so as to enable utility companies to manage the user-side electrical loads and also consumers to voluntarily lower their demand for electricity. Alternative to connecting more conventional generators to the electrical power system, DSM programs pay electrical energy users to lower their energy consumption. The utilities around the world pay for DSM capacity because it is generally more economical and uncomplicated to acquire than conventional generation[3]. DSM is a set of flexible and interconnected programs that permits customers a substantial role in decreasing their general usage of electricity and shifting their load during peak times and this fosters better efficiency and operations in electrical energy systems[5]. DSM activities, which are classified into; energy response (energy efficiency and conservation (EEC)) and demand response (DR), as shown in Figure 1.1, are becoming more popular due to technological advances in smart grids and electricity market deregulation [13].

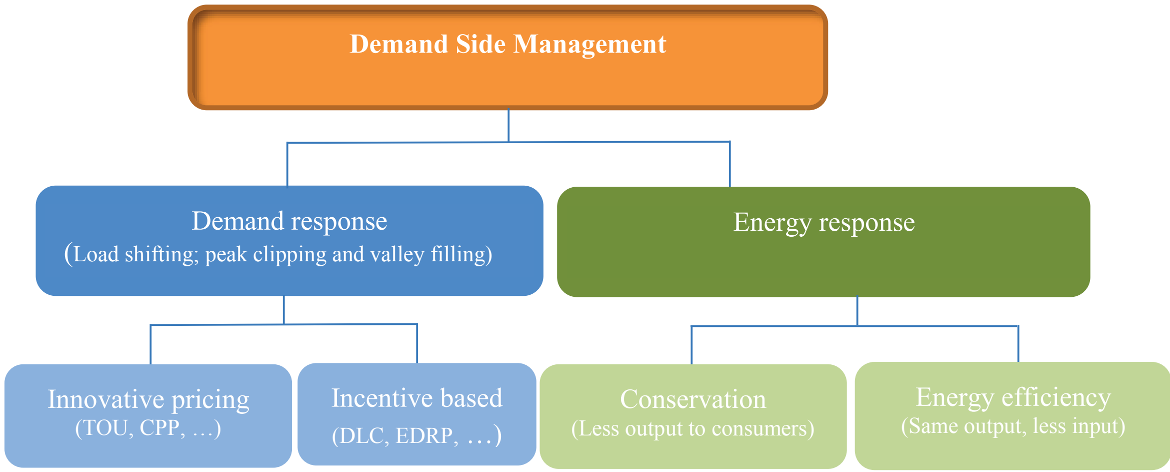

Figure 1.1: Demand side management components

[5]Sustainable energy regulation and policymaking for Africa, Module 14; Demand side management.< http://africa-toolkit.reeep.org/modules/Module14.pdf>

Energy efficiency and conservation programs entail encouraging customers to give up some of their energy usage [14–18] in order to gain some economic benefits. The energy reduction can be achieved through activities such as reducing the settings of thermostat [19, 20] or retrofitting projects [21–23] such as replacing incandescent with energy saving bulbs.

Demand response (DR) on the other hand is a highly flexible program that can be customized to the energy consumption and financial objectives of participants. DR is defined as the reduction in the consumption of electrical energy by customers from their expected consumption in response to an increase in the price of electrical energy or to incentive payments[6,7]. DR options are generally categorized as price-based and incentive-based programs [24]. It is expected that demand response will be an important stepping stone towards practical deployments of the smart grid [10].

EEC and DR are quite different; EE reduces kilowatt-hours used or it is an energy saving strategy which uses less energy to provide the same service, while DR reduces kilowatts of demand during peak hours of the day and both benefit in cost savings [25]. Although DR alone can only help in load shifting rather than energy savings [26], it can promote energy savings when used in conjunction with renewable energy, storage together and some incentive [27, 28]. DR pays customers for reducing load during events, while EE involves an initial investment repaid over time through lower energy bills. The combination of the two can provide synergy: Combining the revenue stream of DR with the energy savings from EE, building owners can get better financial outcomes than with either approach alone.

Due to the complex interactions between residential customers and the power utility companies, DSM has often been studied using various techniques [10] from game theory [29, 30], optimization, and microeconomics [31, 32]. The optimization of energy consumption, with consequent cost reduction, is one of the main challenges for the present and future smart grid [33]. In this work, residential DR is studied using the optimization approach. In the optimization approach, load shifting is proposed where a consumer attempts to find the best way to schedule their resources depending on the electricity tariff provided by the utility. In this thesis, it is shown that, under such a setting, whenever customers have enough trans-

[6] FERC, Demand Response Compensation in Organized Wholesale Energy Markets.<http://www.ferc.gov/eventcalender>.

[7] V.E. CapGemini Consulting Tech., Demand Response: A Decisive Breakthrough for Europe CapGemini Consulting Tech., 2009.< http://www.capgemini.com/insights-and-resources/by-publication//>

ferable appliances, significant energy savings can be achieved. With proper modelling of appliance usage in a household as well as taking into consideration the consumer's options of inconvenience, budget and proper coordination of appliances has been shown in this study that it affects the appliance scheduling problem. Today the world is moving towards cleaner energy strategies which are inevitable in smart grid applications. Therefore, it has also been shown in this work that by incorporating the storage and PV generator the consumer can further increase cost savings and reduce their electricity peak consumption as well as the total energy drawn from the grid. Insights on the complexity of the optimization problem are provided, to allow the customers to better determine the trade-off between complexity, cost, and the need to schedule their energy resources. The derived models provide a blueprint for integrating demand-side management and resource-level scheduling.

Initial research on DR programs focuses on large consumers, commercial and industrial due to their large consumption [34]. Residential demand response (RDR) has also contributed significantly to energy reduction, as has been proved by some experiments[8,9] [35]. Consumer participation is achieved by varying electricity prices as well as offering incentives [36] and this in turn promotes system load balancing as a result of load shifting and curtailment, which is vital for load reduction during peak times. Since DR was initially created to manage peak load, it has been found in the USA that the residential segment simply cannot be ignored as part of any utility's energy management strategy. RDR diverts money that would generally go to a fossil fuel power plant to homeowners instead through peak shifting/shaping and better management of demand. Because of the foregoing; RDR also promotes reduction on environmental impact from the electrical power system due to reduced commitment of peaking plants.

Developing applicable models of residential resources for smart grid applications is a critical issue to allow practical models of electrical energy usage patterns [37]. Many household energy appliances and sources scheduling models have been formulated as different kinds of optimization problems [25, 26, 28, 38] albeit with shortfalls.

[8]The Battle Group, Quantifying demand response benefits, Energetics, 27 January 2007. <http://sites.energetics.com/MADRI/battlegroupreport.pdf>

[9]A. Faruqui, S. Sergici, Discussion paper: the power of experimentation the new evidence on residential demand response, The Battle Group (2008). < https://www.aham.org/GetDocumentAction/id/50282>

1.2 RESEARCH OBJECTIVES AND SCOPE

The objectives of this research are to formulate an optimal control mathematical models on household load and sources under demand response. The mathematical models are formulated to help the residential consumer to save costs during a demand response program and also to help the utility to balance the power system. The systems studied in this research are; a single household with controllable loads, a single household consisting of all the three types of loads, flexible, inflexible and night time loads. In this case the household is installed with a battery as a storage system. Lastly multiple households are considered with each house installed with a dedicated PV and storage system.

The hypothesis of the study is that household consumers can gain economic advantage when their electrical energy resources and loads are controlled optimally during a time differentiated electricity price. This also accords the utility companies the advantage of levelled demand or reduced peak consumption. Other areas that need attention in order to further enhance the solutions of the research question are also investigated.

This research focuses on the development of optimal control models in order to obtain insight into the following issues:

- Optimal appliance scheduling under TOU electricity pricing strategy
- Effect of monetary incentive during peak times
- Inconvenience cost
- The effect of customer budget on consumption and energy cost saving
- Effect of storage systems on levelling of the energy consumption and cost savings
- Effect of PV generator and storage on energy consumption and cost savings.
- Effect of co-optimization of energy cost and carbon emissions on consumption patterns

1.3 RESEARCH CONTRIBUTIONS

This research has contributed in the global study on household energy management and control under a time differentiated electricity price in the following ways;

1. The first contribution of this research is in the development of an optimal control model on household load scheduling. Because of the complexity of the models in this area most literature has simplified these models to linear models. This research has extended these models to mixed integer nonlinear optimization problem.

2. This research has incorporated the inconvenience cost which measures the disparity between the baseline switching status obtained from field measurements to the solution proposed by the simulations. In this work, the impact of the inconvenience cost coefficient on the overall results is also investigated and found to affect the energy cost saving. The importance of this investigation, which has not been carried out in related work, is that consumer participation in a DR program may be affected by the degree at which they are willing to be inconvenienced by the proposed optimal solution.

3. Coordination of appliances, which is incorporated in this research, is also hardly covered by the literature. These coordination models are crucial to the appliance scheduling problem because practically some appliances operate relative to another.

4. In this research, the effect of incentive offered during peak times in addition to time differentiated electricity prices have been investigated. It was found out that consumers may be willing to curtail their electrical load during peak times in response to the incentive.

5. It is also found out that a battery storage system can be used to balance the power consumption in a household and reduce costs if scheduled optimally.

6. In this work, sensitivity analysis is performed to determine the effect of the consumer's willingness to pay, budget, on the energy cost saving. This analysis has not been performed in any of the literature in this area.

7. Development of an optimal control model to investigate the joint influence of energy cost due to appliance scheduling and carbon emissions is also carried out in this research. It is

realised that carbon emissions costs could give customers an environmental motivation to shift loads during peak hours. It is also demonstrated that the consumer's preference on the cost objectives of energy, inconvenience and carbon emissions affects the energy consumption pattern and hence the cost. These results are important for both the consumer and the electricity suppliers, as they illustrate the optimal decisions made in the presence of multiple sub-objectives.

8. Investigation of optimal control of aggregated consumption by multiple household has also been carried out in this work.

9. Field measurements are carried out to obtain baseline consumption patterns.

1.3.1 Publications

The journal publications and conference contributions from this research are:

1. D. Setlhaolo, X. Xia, J. Zhang, Optimal scheduling of household appliances for demand response, Electric Power Systems Research 116 (2014) 24-28.

2. D. Setlhaolo, X. Xia, Optimal scheduling of household appliances with a battery storage system and coordination, Energy & Buildings 94 (2015) 61-70.

3. D. Setlhaolo, X. Xia, Combined demand side management with coordination and economic analysis, International Journal of Electrical Power and Energy Systems 79 (2016) 150-160.

4. X. Xia, D. Setlhaolo, J. Zhang, Residential demand response strategies for South Africa, IEEE PES PowerAfrica Conf., 9-13 July 2012, Johannesburg, South Africa.

5. D. Setlhaolo, X. Xia, Optimal scheduling of household appliances incorporating appliance coordination, Energy Procedia 61 (2014) 198-202.

6. D. Setlhaolo, X. Xia, Optimal scheduling of household appliances for household energy management, 9^{th} International Conference on Green Energy (IGEC-IX), 25-28 May 2014. Tianjin, China.

7. D. Setlhaolo, X. Xia, Residential demand response with carbon emmissions, 1^{st} International Conference on Innovation for Sustainability under Climate Change and Green Growth/Economy, 26-28 May 2015 Johannesburg, South Africa.

8. D. Setlhaolo, X. Xia, Optimal household energy management, 10^{th} Southern African Energy Efficiency Convention, 11-12 November 2015, Emperors Palace, Johannesburg, Gauteng, South Africa. 1^{st} **Prize poster award.**

1.4 THESIS LAYOUT

This thesis is organised in six distinct chapters as follows.

Chapter One is the introductory chapter of this thesis. In this chapter problem statement, study motivation and research contributions of this study are provided.

Chapter Two provides an extensive literature review on this study and shows where this study fits within the bigger picture of demand side management.

Chapter Three provides preliminary results on household appliance scheduling under DR program. An optimization mathematical model is formulated with energy, incentive and inconvenience as the sub-functions with the aim of according the consumer some economic benefits and reduce inconvenience brought by the optimal solution to the baseline appliance commitment. Also the utility benefits from levelized energy consumptions due to load shifting and curtailment. The consumer's main objective is to optimally schedule appliances as per the time varying electricity price. In this chapter the effect of offering incentive during peak times is investigated as well as the consumer's inconvenience. The validity of these formulated models and the effect of the consumer's different preferences regarding energy cost saving and inconvenience is also investigated.

Chapter Four begins with providing background on household appliance coordination and battery energy storage systems. The effect of considering coordination of appliances and the use of a dedicated storage system is modelled and investigated. The validity of this formulated model and the effect of customer's budget or willingness to pay on model solution is investigated.

Chapter Five provides an overview of residential demand response with dedicated PV generator and battery storage. The study in this chapter is performed on aggregated households. In this chapter the study is twofold; the first part proposes an energy management system that combines demand side management strategies with a view of minimizing the consumer's cost and reducing the power consumed from the grid. Appliance scheduling with a dedicated PV generator and storage system under time-of-use tariff shows that customers can realize cost savings and the power demanded from the grid is reduced by scheduling power usage optimally. In the second part of this study, a model is developed to investigate the joint influence or co-optimization of energy cost and CO_2 emissions. In this chapter, economic analysis is also performed.

Chapter Six presents a summary of all the work that has been carried out in this research. Subsequent to the summary, the research conclusions that were drawn from this study as well as recommendations for future work are provided.

Additional materials used in this work such as questionnaire, energy monitoring devices and other related supplementary materials are included in the appendices.

CHAPTER 2

LITERATURE REVIEW AND BACKGROUND STUDY

2.1 CHAPTER OVERVIEW

This chapter provides literature review and background study on residential energy control under demand response as a demand side energy management strategy within which the topic of this thesis falls.

2.2 DEMAND RESPONSE

According to the US Energy Information Administration's 2013 Annual Energy Outlook report, the residential sector currently makes more than 20% of total energy demand and is increasing by 24% worldwide[10] [39]. This shows that residential energy use makes up a sizeable portion of the energy consumption. Since demand response (DR) was initially created to manage peak load, it was found out that the residential segment simply cannot be ignored as part of any utility's energy management strategy. Household appliance scheduling is a basic problem in DR, that can contribute in energy reduction at a time when the system is under stress and also benefit consumers in reducing their energy cost[11] [40].

Demand response is defined as; the reduction in the consumption of electrical energy by end users from their expected consumption in response to an increase in the price of electric energy

[10] Residential demand response infographic. <http://www.comverge.com>

[11] W. W. Hogan, Providing Incentives for Efficient Demand Response, FERC EL09-68-000, 2009. <http://http:www.hks.harvard.edu>

or to incentive payments[6,7]. Depending on the configuration of generation capacity, DR may also be used to increase the load at times of high production and low demand. Initially DR programs around the world were applied to large consumers, commercial and industrial, and much of research has been done to quantify the impact of such programs[8] [34, 41], however both technological and policy challenges still remain. DR participants have both financial and reliability benefits. Additional benefits include; more robust retail markets, additional tools to manage customer load, risk management, market performance, linking wholesale and retail markets and environmental benefits[12].

2.2.1 DR options

Demand response options are mainly classified into two categories as shown in Figure 2.1. Price based DR programs depend on consumer's choice to participate by varying their consumption in response to price signals from the utility. These programs are a way of providing consumers with a choice to divert from the conventional flat pricing and to encourage an efficient electricity market. Customers who are equipped with this information about DR have a tendency of reducing their electricity consumption during high price periods. Incentive based DR are reliability programs that offer incentives to customers who lower their consumption during periods when the system is under stress or when needed [24, 42–44]. These programs aim at providing economical benefits to both consumers and suppliers as well as environment and reliability benefits to the entire world.

2.2.1.1 Price based DR

These are innovative time-based electricity pricing strategies where the utility varies the price depending on the time-of-day, the day and status of the electricity network when the service is provided. The general logical context of time-based pricing strategy is the anticipated or observed change of supply and demand balance of the electrical energy. The time-based pricing strategies include fixed TOU or dynamic pricing that reflects the current supply-demand status of the electrical energy system, RTP, and status of the electricity network (CPP, EDP, ED-CPP) programs.

[12] Global Energy Fund, The Electricity Economy; New opportunities from the transformation of the electric power sector, August 2008.< http://www.globalenvironmentfund.com/media-room/reports/>

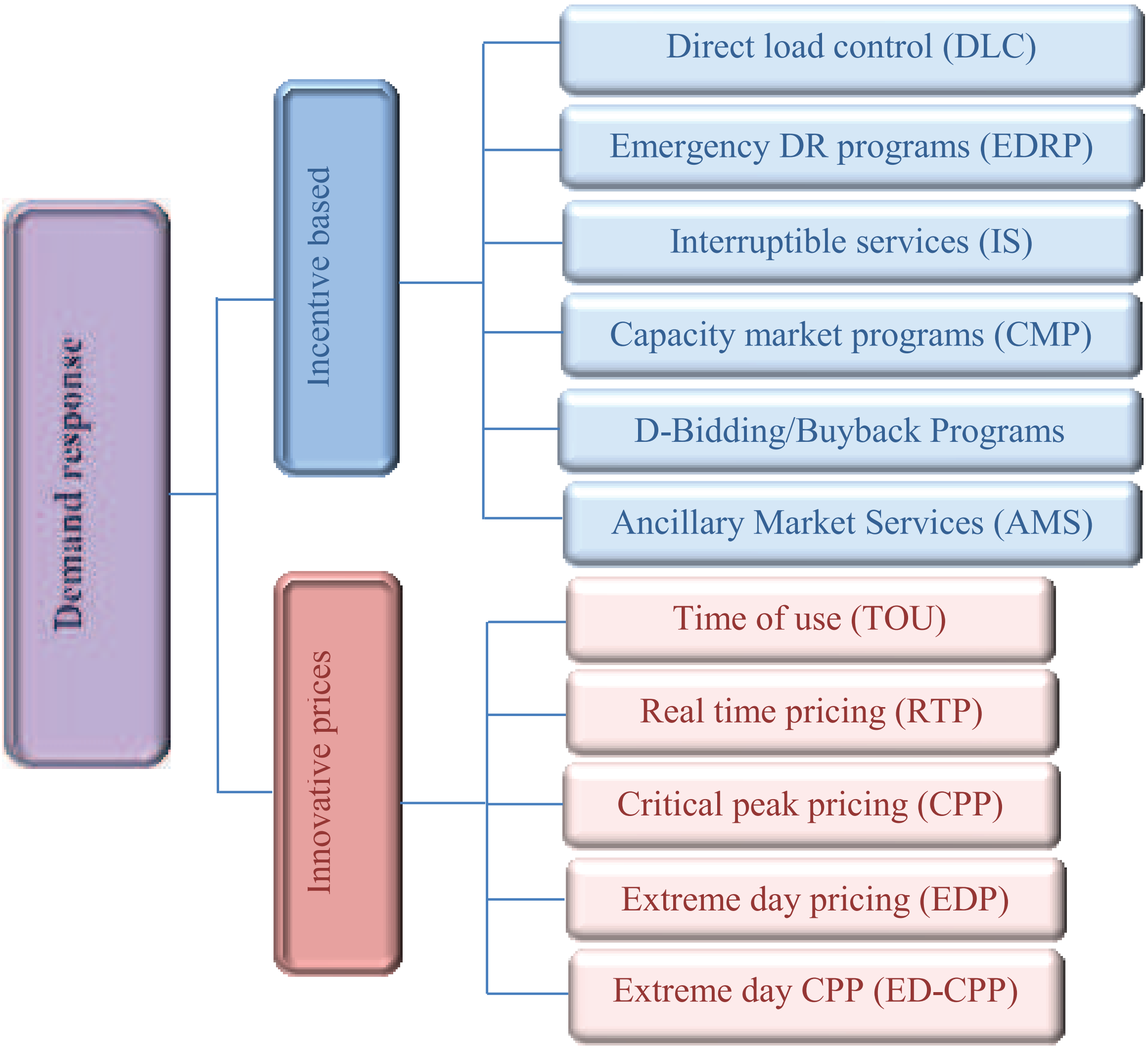

Figure 2.1: Demand response options

Time-based pricing for the provision of electrical power includes, but is not limited to the following because both categories' can be designed to achieve complimentary goals:

Time-of-use (TOU). The consumers are informed in advance on the electricity cost arising from the energy consumed during the TOU periods. This strategy enables the consumers to adapt their electricity consumption behaviour in line with the varying costs. This adaptation is meant to manage the cost incurred by shifting to cheaper periods or reducing overall consumption. The TOU pricing strategy has different energy rates and the simplest rate typically involves only two pricing seasons, with higher rates for peaking season. An intricate time-of-day tariff involves two or three pricing periods within a day namely; off-peak, standard and peak periods. Highly complex and sophisticated rates however, may have a number of shoulder periods and seasonal variations. Typically, South Africa's only utility, Eskom, has a two rates TOU strategy called Homeflex for some urban residential consumers. Homeflex TOU pricing strategy has two different time periods in a year as shown in Table 2.1; high demand period during winter months (June-August) and low demand period (September-May). In each season, energy charges for the times of day differ according to the two rates; peak (07:00-10:00 and 18:00-20:00) and off-peak on other times[13]. The units c/kWh is South African cents/kWh.

Table 2.1: Homeflex TOU tariff structure for energy charges

2011/12 **Energy charge**	**Summer** (September-May) Low demand season	**Winter** (June-August) High demand season
Peak c/kWh	65.86	174.87
Off-peak c/kWh	43.89	55.10

Real-time pricing (RTP). This DR pricing strategy features prices that vary hourly or sub-hourly (generally 10-15 min time intervals) [45] all throughout the year and it may be for some or the entire load of the customer. The utility or retailer notifies customers of the rates on an hour or day-ahead basis reflecting the utility's actual cost of generating and/or purchasing electricity. Compared to TOU, RTP pricing strategy does not fix the price or the time period in advance; hence it is a dynamic pricing strategy.

Critical peak pricing (CPP). This innovative pricing strategy has substantially high rates during a few critical hours of the day or year. These are called when the utility anticipate power system emergency conditions or high wholesale market prices and they are called either on the day of the critical peak or a day before.

Extreme day pricing (EDP). This pricing strategy is like CPP but with the exception that higher rates are applied in all hours of the day for all critical days of the year. The timing of these hours is not known until a day ahead.

Extreme day CPP (ED-CPP). These pricing strategies are an alteration of CPP because the

[13] Eskom, Homeflex.<http://www.eskom.co.za/CustomerCare/TariffsAndCharges/Documents/Eskom%20Booklet.pdfp>

peak rates only apply to the critical peak hours on extreme days. There is however no TOU on the remaining days.

Each of these innovative pricing strategies exposes consumers to varying quantities of electrical energy prices. Consumers have a chance to reduce more of their expected electrical energy price by participating in high risk priced based DR programs. For example, dynamic rates such as RTP are perceived to be the riskiest from the consumer's point of view because they are exposed to wholesale real time prices. However, the consumers on dynamic pricing strategy will most highly be exposed to lowest average prices.

TOU pricing strategy has less uncertainty to consumers because consumers have the knowledge of the actual rates and the time at which they will be active well beforehand. This also applies to rates that vary seasonally. Although TOU pricing strategies generally provide higher price and time predictability in comparison to the dynamic pricing strategies, they have highest average price.

2.2.1.2 Incentive based DR

Incentive based DR programs are instituted by the electricity suppliers, transmitters and distributors. These programs offer incentives to the customers on their curtailed loads that may be added to or separated from their normal retail electricity rate. The incentive offered may be time-varying or fixed. When the grid operator anticipates a threat to power system network reliability condition or when the energy prices are high, the load curtailments are needed from consumers. Most of these programs do have tools in place to determine the consumer's energy consumption baseline, so retailers and the utility can monitor the extent of the reaction customer's load. In some of these programs, there is a monetary penalty imposed on customers that fail to fulfil the requirements after contractual obligation when events are broadcasted [41, 42, 46]. In exchange for a reduced load, utilities offer consumers an incentive payment or bill credit.

Direct Load Control (DLC). These refer to programs where utilities or system operators remotely "cycle" (turn off) consumer's high consuming electrical equipment such as air conditioners and electric water heaters (for residential) for a limited period of time to address power system reliability contingencies.

Emergency Demand Response Program (EDRP). These are primarily employed during reliability-triggered events which causes reserve shortfalls. Consumers can opt for non-participation by not reducing their loads thereby forgoing the incentive to be earned. Under these programs, payment rate is typically specified ahead of time.

Capacity Market Program (CMP). CMP incentive programs are programs where customers mainly pledge to allot their pre-specified electrical energy load curtailment as substitutes for system capacity. Consumers who do not comply with their agreement are subject to penalties. These types of incentive based DR programs can be viewed as some form of insurance [41]. As a trade-off for their commitment to reduce their energy load when ordered to do so by the load serving entities, they receive guaranteed payments. These programs are comparable to insurance because participants are paid to be on call or standby even though load curtailment may not be announced in some periods.

Interruptible/curtailable service (I/C). Customers who participate in I/C service programs receive a bill credit as a trade-off for an agreement to their electricity load curtailment when the system is under stress. Consumers may be penalised for non-curtailment. Since the I/C tariffs structure is offered by the utility, it differs from the EDRP and CMP incentive programs. Traditionally, I/C programs have been offered only to the high energy consumption customers such as industrial and commercial.

Demand Bidding/Buy Back. These demand bidding/buyback DR incentive programs are mainly offered to large consumers of typically 1 MW or more. They primarily encourage them to offer bids to reduce their loads as per the wholesale electricity market prices. Alternatively, the customers identify the amount of electrical load they would like to reduce at advertised rates. These programs give a way to kindle consumer's reaction to price increase. If the customer's offer is lower than the bids of the suppliers, the load cuts are executed and consumers are compelled to reduce their electrical energy consumption. The programs are generally interesting to a lot of consumers because they permit them to receive higher payments for their reduced load high rates even though they remain on fixed rates.

Ancillary Service Markets (ASM). In ancillary-service market programs, customers bid for load reductions as operating reserves in ancillary markets handled by the grid operators such as Independent System Operator (ISO) or Regional Transmission Organizations (RTO). The consumers whose offers are received and approved are paid the market price for their standby commitment. At a time when the customer's load reductions are required, notification is sent to them by the grid operators and may be paid the spot market energy price. The requirement for customers who participate in ASM markets is that they must be able to adjust their load promptly upon an occurrence of a reliability event. The response time is preferably within minutes rather than hours because it depends on the kind of the reserve being met and the type of event.

These two categories of DR programs are interconnected and the various programs under each category can be designed to achieve complimentary goals. A combination of EDRP and RTP, and EDRP and TOU programs have been demonstrated by [34, 41]. In this thesis, the study of RDR modelling is studied considering TOU tariff as well as incentive during peak periods.

2.2.2 Requirements for an effective DR

A DR program requires enabling technology for information accessibility, control and communication between participants. In addition a robust policy framework is needed for proper coordination and management of these programs. These are further elaborated below.

2.2.2.1 DR enabling technology

A key factor in household electrical energy management under a demand response for smart grid applications is the enabling technology or an automatic energy management system that allows the utilities, homeowners, and others participants to monitor, manage, control and cut down on energy usage [47, 48]. The system consists of hardware and software. The hardware importantly consists of the communication network that allows multiple household appliances to be interconnected and individually identifiable by the processor. The processor solves the optimization problem by optimizing the operation and scheduling of appliances such that the least cost is achieved under given conditions [27]. The software however, is a solver in which a predefined optimization model is solved. Although it may be true that most of the communications and monitoring technologies needed for the general DR are currently available, the challenges still remain with the optimization and control [11]. Developing applicable models of residential loads for smart grid applications is a critical issue to allow practical models of electrical energy usage pattern [37].

Advanced metering infrastructure (AMI) is a DR enabling technology. It includes two way communication networks, advanced meters and database management systems. A two-way AMI is capable of providing energy efficiency and cost savings through automated remote smart meter readings and remote outage detection, diagnosis, and restoration [49]. In addition, electric utilities or load serving entities can dispatch price signals to "smart" appliances to inform them about an anticipated forthcoming high rates period. Depending on the consumer's reaction, optimal commitment of smart appliances can lower the energy consumption through shifting of the load to lower-cost periods. This load shifting is done until the high-cost period has ended. A two-way AMI communication networks has a greater capacity to support various forms of DR[6].

2.2.2.2 Home area network (HAN)

HAN is a type of local area network located within the user's home and its multiple in-premise appliances to be interconnected and individually identifiable. This accords the AMI system individual home appliances load control, enhanced ability to measure, verify and dispatch DR, and display feedbacks to consumers showing the itemised billing effects associated with usage of various appliances[14] [50, 51]. Therefore, it is the backbone of the communication between smart meter and household appliances. A typical home with HAN is shown in Figure 2.2 that portrays the complex architecture of such a system. The basic components as shown in the figure consist of: 1) The gateway that connects external information services to the HAN. 2) The access point that form the wired or wireless network itself. 3) The network operating system and network management software. 4) The end points such as thermostats, meters, in home display devices, and appliances.

The importance of a HAN in smart grid Energy efficiency, demand response, and direct load control are key components in realizing value in a Smart Grid deployment. Behavioural energy efficiency utilizing real-time meter data, technology-enabled dynamic pricing, and deterministic direct load control are examples of demand-side management applications that are enabled by high bandwidth, two-way, end-to-end communications in the Smart Grid. A

[14]Renesas, Renesas Solutions for Smart House/HEMS Product Development.< http://www.renesas.com/edge_ol/features/11/index.jsp>

Smart Grid that incorporates energy efficiency and demand response increases its value as a long-term infrastructure investment and reduces the time required to achieve a satisfactory return on investment in the short-term. The HAN is a subsystem within the Smart Grid dedicated to demand-side management (DSM), including energy efficiency and demand response. A number of HAN aspects influence the Smart Grid infrastructure:

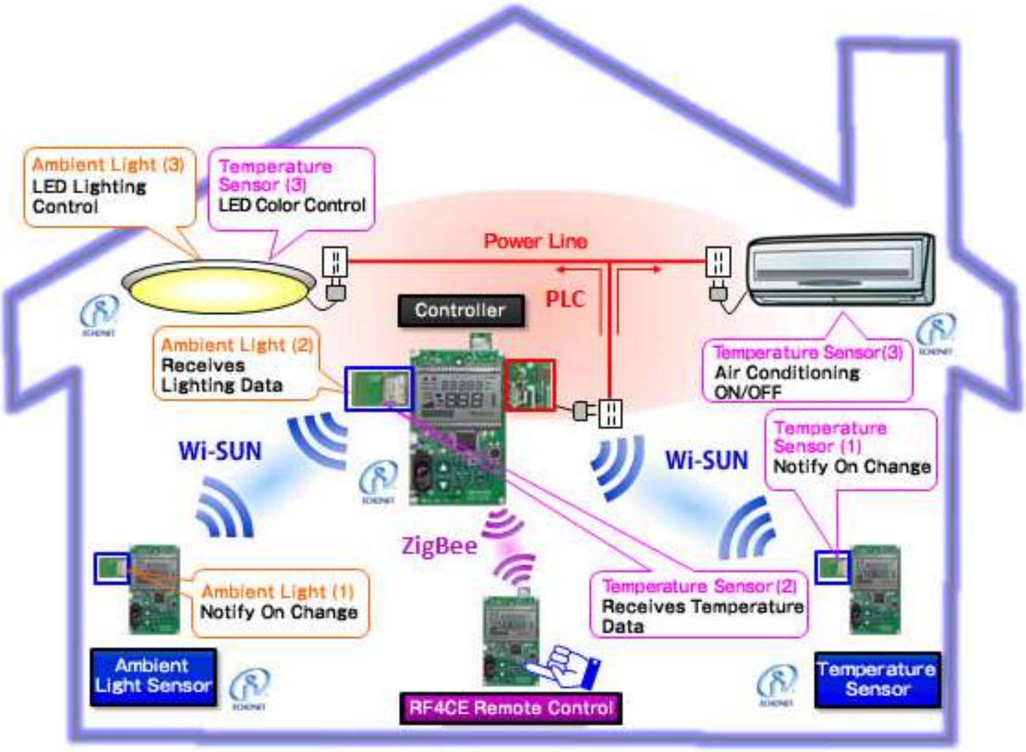

Figure 2.2: Typical smart home with HAN for smart grid applications. Adapted from http://www.renesas.com/edge_ol/features/11/index.jsp, with permission.

2.2.2.3 DR policy framework

For coordinated and optimal operation of any DR program, a robust and coherent policy framework is required. The purpose of this framework is to manage all assets and acquired services and its associated policy instruments. The framework set the direction for the entire management of the DR program to ensure that the performance of these activities offer value for money and demonstrates sound stewardship in the delivery of the program. The consequence of failure to properly manage and control these activities can result in increased program and administrative costs, and the likelihood of compromising the outcomes of the program. In addition, the framework pinpoints key policy instruments, professional ethics, legislation, standards and requirements for integrated information systems that comprise the basis for the management practices and controls [12, 52, 53].

2.2.3 Mathematical modelling of residential DR

2.2.3.1 General modelling of RDR

The electricity consumption in a household primarily depends on the power consumption of the electrical appliances and the behaviour of the occupants using them [54–56]. Two approaches to residential load profile modelling are presented by the literature: top-down and bottom-up approaches [57–61]. The granularity of data in these two methods differs; the former offers aggregated data whereas the latter offers fine and more informative data in the area of household energy management. The top-down model is not concerned with individual end-uses and their activities or behaviour [57, 62, 63]. Although top-down models rely on readily available historic, aggregated energy data, which makes them straight-forward to implement, this approach however, makes it harder to model changes in energy consumption because of lack of data on how energy is consumed, therefore it makes it difficult to recommend changes related to behaviour. In the bottom-up model, the load is constructed from households' individual appliances. This model has been shown to offer high resolution to load modeling [58–61]. In this thesis, formulation of optimization model for residential energy consumption under demand response is carried out using a bottom-up approach through individual appliance scheduling. It has been stated in [61] that in residential energy modelling, the bottom-up method promotes efficiency.

Developing applicable models of residential loads for smart grid applications is a critical issue to allow practical models of electrical energy usage patterns [37]. Due to the complex interactions between residential customers and the power utility companies, DR has often been studied using various techniques [10] from game theory [29, 30], optimization, and microeconomics [31, 32]. The optimization of energy consumption, with consequent cost reduction, is one of the main challenges for the present and future smart grid [33]. In this work, residential DR is studied using the optimization approach. Non optimal control modelling methods have been proposed in the literature with [54, 56] or without consideration of the consumer's behavior [64]. In [56] office occupant electricity consumption behaviour is studied through a developed data mining approach. The following literature review subsection focuses on the optimization mathematical modelling method adopted in this thesis. The advantage of this method is that it offers optimum solution.

2.2.3.2 Optimization modelling of RDR

Research on residential demand response models for smart grid applications is currently ongoing. In this thesis we portray the optimization mathematical models using Figure 2.3. Formulation of an optimization model generally involves identifying inputs and outputs of a desired model. Where the model could be deterministic or stochastic. A stochastic model considers uncertainties while deterministic does not and in this thesis, deterministic models are adopted because stochastic modelling is outside the scope of this thesis.

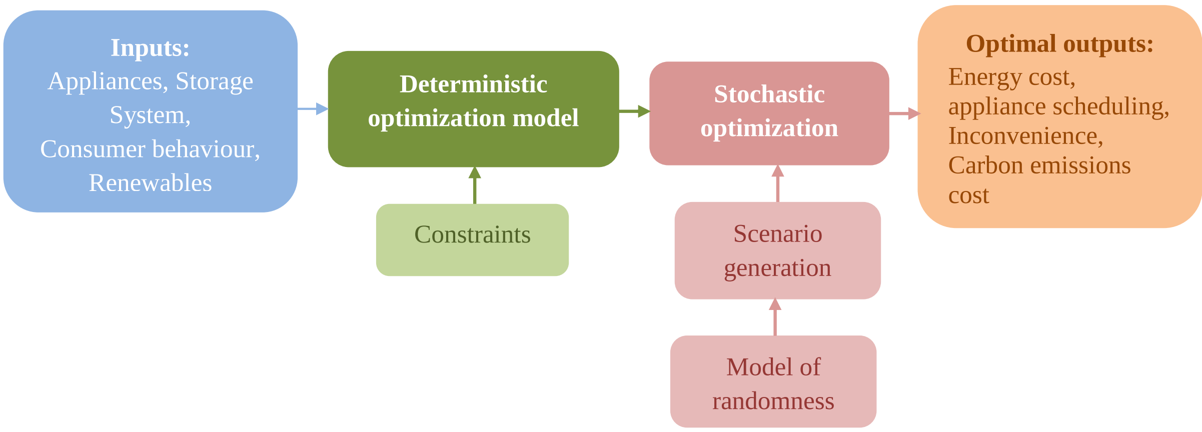

Figure 2.3: General layout of RDR optimization modelling

The general case of a user DR model that provides the basis for RDR is provided by [38], where home appliances are classified into four major groups and the model is a structure of utility functions and consumption constraints for appliances. The utility functions of these different appliance categories have been provided and the general objective is to maximize social welfare. However, the paper provides a general framework formulations and is thus not directly implementable. Advancement in RDR has gained momentum recently. A novel energy management system for RDR, the consumer automated energy management system (CAES), which is an on-line application system, has been proposed in [65]. The objective of the system is to minimize the electricity cost for operating appliances. In [66] mixed integer linear programming (MILP) is used to schedule home appliances in order to minimize the electricity cost. It is shown that a financial incentive can encourage residential consumers to control their loads, as demonstrated by application of a plug-in hybrid electric vehicle (PHEV) in [67]. The practical model of day-ahead scheduling of appliances is shown in [68]. This model is applied to the scheduling of electric water heaters (EWH) subject to the respective constraints.

General models on household appliance scheduling without storage or renewable energy generators are also presented in [25, 40, 68–72]. These models primarily present household appliance scheduling under demand response programs for smart grid applications. In [26, 28], the scheduling problem is presented with a storage system either as a battery or PHEV; the models of storage systems are also presented in [73, 74]. A number of times the application of photovoltaic (PV) and battery storage is considered without the scheduling problem, hence as optimal scheduling of resources of various combinations of PV/wind/diesel/battery system [75–82] on a distribution network. However, the shortfall of these models is that they are presented as a simplified problem as linear problem (LP) or mixed integer programming (MIP) problems, thereby forging some practical sub-functions and constraints. Despite these efforts, challenges on modelling still remains because of the complex interactions between residential consumers and the power utility companies. Optimization of energy consumption with consequent cost reduction still remains one of the major challenges for the present and future smart grid [33].

This research formulates a practical optimization model for a household energy management and control to determine the optimal scheduling of home appliances under TOU electricity prices. Other areas that need attention in order to further enhance solution are also investigated. This problem is modelled as a mixed integer nonlinear program (MINLP) optimization model with more practical operational constraints. The effect of a battery storage system, PV and carbon emission are also investigated. Sensitivity analysis is performed on a number of parameters to determine their impact on the solution. This research initially focuses on one household and then considers aggregated households.

In this study a model is also developed to investigate the joint influence of price and CO_2 emissions in a DR program and the motivation for this is that consumption habits may require other incentives to change rather than the proposed financial incentive. This joint influence is rarely covered by the literature. Knowledge of carbon emissions can incentivise investment in renewable energy at household level. Governments can save lives and protect communities from the threat of climate change by putting a price on carbon through a carbon tax[15]. In [83], the problem is presented as a multi-objective problem between two subfunctions of cost minimization through appliance scheduling and carbon emissions. The model is solved as a Markov-chain load model in order to forecast the power demands of residential consumers and a scheduling program for providing optimal schedules for smart appliances. In this research, the problem is presented as an LP problem, as both sub-functions and constraints are linear. In [84], the thesis evaluates two formulations to schedule smart home appliances with respect to economic and environmental benefits. The thesis also focuses on the reduction of computational time for the scheduling of smart home appliances as a mixed integer linear programming (MILP) problem. In [84], the dynamic data for carbon footprint is available, obtained from the Institution of Ecology at the Royal Institute of Technology. In South Africa, however, there is currently a fixed rate of carbon emissions. A similar model to this work is also presented in [85]; where a solution is proposed that models a multi-carrier energy system in a smart grid with appliances scheduling, gas (CHP) and carbon emissions. The objective is to determine an optimal policy that attains many rewards in the long run, where the Monte Carlo method is used.

2.3 STORAGE AND RENEWABLE ENERGY SOURCES

2.3.1 Storage system

Battery energy storage systems (BESS) are an option to provide peak shaving and valley filling of the residential load profile [86, 87]. Electric vehicles and conventional batteries have over the years been used as residential energy storage devices [88]. There are two main applications of BESS in the residential sector. Firstly there is the off-grid hybrid energy solution, where two or more different types of renewable energy sources are integrated together with a storage device. This method is mostly applied to rural settlements where there is no access to the grid power [89–91]. This has been extensively studied in literature [90, 91]. The second application of BESS is a backup system for a household connected to the grid[19]. This application is motivated by unreliable and intermittent electrical power supply. In this

[15] S. Blaine, SA first African country to introduce carbon emissions tax, BDLive, 28 February 2013 <http://www.bdlive.co.za/national/science/2013/02/28/>

[19] PowerGen renewable energy $< http://powergen-renewable-energy.com/ >$

application the BESS is connected to the grid. It can be available as a compact backup electronic power supply system, interruptible power supply (UPS). Usually in an African set-up, buying a UPS is not affordable to many because of its high cost due to its technological enhancement features such as longer life and less maintenance. The ideal solution is to build the system. These systems can be designed in any size, based on the application.

In [92], a detailed design of flat plate lead acid batteries for the study of power flow management for grid interconnection of PV and batteries has been carried out. In these references [92, 93]; a detailed model of the battery as a storage system connected to PV system under given regulatory conditions is presented, also battery sizing is performed [93]. Although these provide in-depth study of the battery, our work however considers elementary usage of the device. The following subsection gives a brief literature review on PV systems.

2.3.2 PV system

The use of renewable energy sources (RES) has become inevitable in today's electrical energy system because of their sustainability and their environmental advantage. In smart grid applications, use of renewable energy sources at residential level cannot be ignored as many countries including South Africa, have rolled out such systems mainly through household roof-top connections.

South Africa has over the years implemented residential rooftop PV systems; however grid connection of small-scale renewable electricity generation is yet to be implemented because South Africa's national energy regulator (NERSA) is currently in the process of developing the regulatory framework on small-scale renewable embedded generation sources and the guidelines on electricity reseller tariffs[27]. Some of the challenges with small-scale renewable generation grid tie include but are not limited to reverse power flows and metering tariff solutions. For this reason, in this work, we consider households with dedicated solar PV and storage systems, without infeed to the grid. Therefore the purpose of the PV is to charge the battery, which will in turn discharge during peak times to relieve the grid.

In [85], the thesis evaluates two formulations to schedule smart home appliances with respect to economic benefits and environmental benefits.

[27] NERSA, response benefits, Energetics, 27 January 2007 <http://www.nersa.org.za/>

When dealing with renewable sources, the time it takes for the investment to reach break even becomes very interesting to consumers. The payback period of investing in such a system is an important determinant of whether to undertake the project, as longer payback periods are typically undesirable for investment positions. Hence, in this work, economic analysis is also carried out to aid the consumer. Residential demand response models integrated with renewable energy sources are an active current global research area for smart grid applications. In [26, 28], the scheduling problem is presented with a storage system either as a battery or plug-in hybrid electric vehicle (PHEV); the models of storage systems are also presented in [73, 74]. A number of times the application of photovoltaic (PV) and battery storage is considered without the scheduling problem, hence as optimal scheduling of resources of various combinations of PV/wind/diesel/battery system [75–82] on a distribution network. However, the shortfall of these models is that they forgo some practical sub-functions and constraints. In our case we have consider a nonlinear inconvenience cost sub-function and nonlinear constraints such as the appliance's continuous operation and the battery's exclusive operation.

2.4 CHAPTER SUMMARY

In this chapter, an extensive literature review on DSM's strategy demand response is covered, the topic under which this thesis falls. The different strategies, benefits and mathematical modelling are reviewed and the area where our research fits is provided.

CHAPTER 3

OPTIMAL SCHEDULING OF HOUSEHOLD APPLIANCES FOR DEMAND RESPONSE

3.1 CHAPTER OVERVIEW

This chapter emanates from our published paper that bears the same title [25]. Residential demand response is studied through scheduling of typical home appliances in order to minimize electricity cost and earn some incentive. A mixed integer nonlinear optimization mathematical model is formulated under a time-of-use electricity tariff. The model formulations consist of the energy cost model, the incentive model as well as the inconvenience. A case study shows that a household is able to shift consumption in response to the varying prices and curtail consumption due to incentive, through which the consumer may realize an electricity cost saving. A sensitivity analysis of the inconvenience cost coefficient is also performed. The analysis reveals that the total cost savings is influenced by the inconvenience coefficient cost. The importance of this analysis is that the consumer is able to choose according to their preferences with regard to the cost and the inconvenience. The results show that; through optimal scheduling of appliances during a time varying electricity tariff, the consumer can reduce their energy consumption during peak times through load shifting. The consumer has an option to reduce their energy cost further by benefiting from peak incentives which in turn they may contribute further in the system energy balance by reducing the peak consumption. The inconvenience could be used by the consumer to gauge how much the proposed optimal solution deviates from their baseline. This factor enables the consumer to have an option on how much they may be willing to be inconvenienced, hence it could affect the level of participation of the consumer in the DR program. The main contribution of this chapter is consideration of the inconvenience level and the sensitivity analysis of the inconvenience cost coefficient to the solution.

The remainder of this chapter is organized as follows: Section 3.3 focuses on defining the problem and the optimization model formulations. Section 3.4 examines a case study used in this paper. The solution methodology and simulation results are discussed in Section 3.5 and lastly a conclusion is drawn in section 3.6.

3.2 PROBLEM DEFINITION AND MODEL FORMULATION

3.2.1 Problem definition

An electricity-consuming household's objective during a DR program is to gain some economical benefits at a certain degree of inconvenience. To achieve this, the consumer's main objective is to be able to schedule appliances optimally as per the electricity price and at a preferred inconvenience level. In this work, in addition to energy cost and inconvenience minimization, we also consider the incentive offered during peak times. For this reason, the objective function is characterized by three sub-functions, the electricity cost minimization, incentive maximization and inconvenience minimization and the formulations are presented in the subsequent subsection.

3.2.2 Mathematical model formulation

Considering a sampling time (Δt) of 10 minutes and a simulation horizon of 24 hours, the mathematical model is formulated in this subsection. This model is an improvement of [68] in that in this work we have considered the incentive and the inconvenience.

$$\min J_c = \sum_{t=1}^{T} \sum_{i=1}^{A} P_i[\rho_t \cdot u_{i,t} - \beta_t \cdot \lambda(u_{i,t}^{bl} - u_{i,t})] \cdot \Delta t, \tag{3.1}$$

$$P_i \geq 0, \beta_t > 0, i = 1, ...A, t = 1, ..., T, A = 10, T = 144,$$

$$u_{i,t} = \begin{cases} 1, & \text{when appliance } i \text{ is on at } t; \\ 0, & \text{when appliance } i \text{ is off at } t. \end{cases}$$

$$\lambda(u_{i,t}^{bl} - u_{i,t}) = \begin{cases} 1, & \text{if} \quad (u_{i,t}^{bl} - u_{i,t}) > 0; \\ 0, & \text{if} \quad (u_{i,t}^{bl} - u_{i,t}) \leq 0, \end{cases}$$

where t is the time index, $t = 1, \cdots T$, Δt is the sampling time and T is the study horizon, which is 24 hours. i is the appliance index and A is the total number of appliances. P_i is the rated power of appliance i. $u_{i,t}$ and $u_{i,t}^{bl}$ are the optimal and baseline on/off status of appliance i at time t, respectively. ρ_t is the electricity price at t and β_t is the incentive at t. The indicator function $\lambda(u_{i,t}^{bl} - u_{i,t})$ denotes a certain state in a model. It is either 1 or 0 to allow consumers to earn an incentive only when they switch off their appliances during peak times. If it is 1 an incentive is earned, otherwise there is no incentive. $u_{i,t}^{bl}$ is the appliance's baseline switching status while $u_{i,t}$ is the optimal switching status. The following constraints are formulated to the objective function (3.1):

$$\sum_{t=1}^{T} \sum_{i=1}^{A} P_i[\rho_t \cdot u_{i,t} - \beta_t \cdot \lambda(u_{i,t}^{bl} - u_{i,t})] \cdot \Delta t \leq C. \tag{3.2}$$

This constraint models the maximum cost that the consumer is willing to incur in one day, C, and it is not more than R25 (R denotes the South Africa currency, rand)(1 Rand = 0.085USD), as at 01 May 2015. This value is obtained from the consumers' electricity bill.

Note that the inflexibility of many loads is usually not absolute, and they might be flexibly adjusted within a range [26, 94, 95]. In this work, we assume that the appliances are flexible within the consumers' specified time ranges. For each appliance, the user indicates d_i and e_i as the beginning and end of the time interval in which the appliance is to be scheduled. N_i is the allowable time interval or the time duration required to finish the normal operation of appliance i. Given the predetermined parameters d_i, e_i and N_i, in order to provide the needed consumption for each appliance in times within interval $[d_i, e_i]$ it is required that,

$$\sum_{d_i}^{e_i} u_{i,t} \geq N_i. \tag{3.3}$$

The constraint below ensures continuous operation of appliances [96]. In this chapter it is applied to all appliances except appliances 3 and 7, the kettle and EWH. Practically the kettle's normal operation does not exceed the sampling time while the geyser is a continuous on/off appliance.

$$\sum_{d_i}^{e_i-(N_i-1)} u_{i,t} \cdot u_{i,t+1} \cdot u_{i,t+2} \cdots u_{i,t+(N_i-1)} \geq 1. \tag{3.4}$$

Additional constraint is needed as follows, allowing operation of one appliance after the other:

$$d_{i2} \geq d_{i1} + N_{i1}. \tag{3.5}$$

The current starting time slot of $i2$ should be after the starting time of $i1$ plus its run time. For example, the clothes dryer follows the washing machine.

The consumer's decision to continue participating in the program may not be determined by only the energy cost saving and the incentive earned, but also by the inconvenience that comes with the new schedule. The scheduling inconvenience (I) seeks to minimize the disparity between the baseline and the optimal schedule. In this paper the postponement and advancement of the schedule are both regarded as an inconvenience. The consumer therefore also minimizes the objective function (3.6), the inconvenience:

$$I := \sum_{t=1}^{T} \sum_{i}^{A} (u_{i,t}^{bl} - u_{i,t})^2. \tag{3.6}$$

The inconvenience level is then included in the main objective (3.1), therefore the modified objective function that the consumer seeks to minimize is expressed as follows:

$$\min J = J_c + \alpha I, \tag{3.7}$$

subject to constraints (3.2)-(3.5), where J_c is defined by equation (3.1), I is the scheduling inconvenience as in (3.6) and α is a weighting factor, which represents how the consumer favors the scheduling inconvenience. It is to be noted that the inconvenience as presented in (3.6) is a unit less value. Therefore to express all sub-functions within the overall objective function (3.7) with the same unit, there is a need to use some form of cost coefficient to express all sub-functions in the same units. In this work we assume that α is a fixed cost value.

This problem has binary control variables $u_{i,t}$, which are the optimal on/off status of appliances, and the inputs are the appliance's rated power P_i , the electricity prices ρ_t, the initial appliances' status $u_{i,t}^{bl}$ and the incentive β_t. The results are the appliances' optimal schedule, the energy cost, the incentive and the schedule inconvenience.

3.3 CASE STUDY

Eskom's hourly electricity tariff has been discretized into 10 minutes, since the model has 10 minutes' sampling time and the optimization is over a 24-hour period. This encourages shorter waiting periods for behaviour change. The scheduling period is achieved by deciding whether to turn on the appliance at the beginning of each 10 minutes. The tariff is based on Eskom's TOU Homeflex structure for residential consumers as shown in Table 3.1. The Homeflex 1 tariff has five charge components. Eskom's peak times are $07:00-10:00$ and $18:00-20:00$[16]. From the information, only energy charges of 174.87c/kwh and 55.10c/kWh for the peak and off-peak high-demand period are used for calculations. A typical household in South Africa has been used as a case study and ten appliances have been selected and studied over a one-month weekday period. These are shown in Table 3.2. Appliance rated power is specified by the appliance manufacturers and can be obtained from the appliances. One month's weekday data on appliance usage in the household under study were collected, as well as the information on the allowable time duration required to finish the normal operation of the appliance, N_i is obtained and the highest value is recorded in Table 3.2. The information on d_i and e_i as the beginning and end of the time interval in which the appliance is to be scheduled is specified by the user, based on the usual or preferred usage and this ties with usage data obtained. This is typical of a working class household where most activities occur in the morning and after work. An incentive of R0.2/kWh is used, which is guided by[17] [70].

[16] Eskom Tariffs & Charges 2011/12.<http://www.eskom.co.za>.

[17] Southern California Edison, Scheduled load reduction program (SLRP) summertime energy management solution with a cool payoff.<http://asset.sce.com/>.

Table 3.1: Eskom's Homeflex 1 tariff structure.

	Charges				
Demand	Service (R/day)	Network (R/day)	Peak energy (R/kWh)	Off-peak (R/kWh)	Envir. Levy (R/kWh)
High	2.45	3.04	1.7487	0.5510	0.02
Low	2.45	3.04	0.6586	0.4389	0.02

Table 3.2 shows parameters used and typically appliance *1* is scheduled twice in a day at least 30 and 50 minutes in the morning and evening respectively. It is to be switched on at any time between t=30 (05:00) to t=42 (07:00) and t =196 (16:00) to t=120 (20:00) respectively. Appliance 2 is scheduled once a day for at least 50 minutes any time from t=108 (18:00) to t=114 (19:00). It is to be noted that the appliance's baseline schedule is included in the results in Table 3.3 for ease of comparison with the optimal results.

3.4 SIMULATION RESULTS AND DISCUSSION

The formulated model is solved with AIMMS software, which uses Aimms Outer Approximation Algorithm (AOA) that utilizes CPLEX and CONOPT as mixed integer programming (MIP) and nonlinear programming (NLP) as solvers respectively. AOA is written with the AIMMS GMP functions and can be customized by users to fine-tune the algorithm for their specific problems. CPLEX is a very powerful tool for solving large and difficult MIP problems and it uses a branch-and-bound algorithm for solving MIP problems. CONOPT is an efficient large-scale NLP solver. AIMMS computes exact second order derivatives, which are used by CONOPT to solve certain classes of NLP models much more efficiently. It was shown that the algorithm finds a global optimum solution in a finite number of steps[18]. The solver offers solutions to problems of the form:

[18] M. Hunting The AIMMS Outer Approximation Algorithm for MINLP,Paragon Decision Technology, Haarlem (2011) <http://www.aimms.com>.

Table 3.2: Appliances data

No.	Appliance	Power rating (kW)	Duration N_i(Mins)	d_i	e_i
1	Stove	3.000	30 50	30 96	42 120
2	Microwave	1.230	10	96	114
3	Kettle	1.900	10 10	33 106	45 120
4	Toaster	1.010	10	30	42
5	Steam iron	1.235	48	96	126
6	Vacuum cleaner	1.200	30	48	62
7	Electric water heater	2.600	120 120	24 96	49 132
8	Dishwasher	2.500	150	120	144
9	Washing machine	3.000	45	96	132
10	Tumble dryer	3.300	30	96	122

$$\min f(x), s.t., \begin{cases} Ax \leq b, A_{eq}x = b_{eq}(\text{linear constraints}) \\ c(x) \leq d, c_{eq}(x) = d_{eq}(\text{nonlinear constraints}) \\ Lb \leq x \leq Ub(\text{variable bounds}) \\ x_i \in \mathbb{Z}(\text{integer decision variables}) \\ x_j \in \{0, 1\}, i \neq j(\text{binary decision variables}) \end{cases}$$

Table 3.3 shows the consumer's baseline and the optimal schedule at $\alpha = 0.1$. It shows that the consumer can redistribute their load from their baseline schedule to different time slots because of variable prices. According to Table 3.3 and Figure 3.1, the stove's baseline schedule is 30 minutes in the morning and evening at t=37 (06:10) to t=39 (06:30) and t=108 (18:00) to t=112 (18:40), respectively. The solution suggests a different stove schedule in the evening at times t=102 (17:00) to t=106 (17:40) and the same time for the morning is maintained. This is logical in that the baseline time is within off-peak times and the inconvenience is minimized. For the second appliance, the microwave, the baseline and optimal switching times are t=108 (18:00) and t=104 (17:20), as shown in Table 3.3. The two appliances' operational times are consecutive, which satisfies the continuous operation constraints (3.4). The EWH is excluded from the continuous operation because practically it is a continuous on/off appliance. Figure 3.1 shows the switching status of appliances with the highest cost, EWH, dishwasher, clothes dryer and stove. The costs are EWH=R7.2214, dishwasher=R3.401, dryer= R2.3846 and stove=R2.18. The high prices are due to their high-rated power coupled with longer operation time or scheduling within peak times. The solid stems show optimal switching status, while the dotted ones show the baseline appliance commitment. Even though the clothes dryer is only on for three slots, the cost is high because it is scheduled during peak time, possibly because it has to follow the washing machine as per constraint (3.5). It can be seen that for the EWH, the morning commitment is the same for both baseline and optimal solution, whereas the schedules are different later due to the optimization algorithm trying to schedule it outside the high-priced period. The rest of the results on the remaining appliances are shown in Table 3.3; others remained in off-peak while a few shifted to overlap both peak and off peak. This is what is expected for the consumer with a wider range of possible starting and ending operational time of appliances, such as in this study.

The simulation results show that baseline cost with $u_{i,t}^{bl}$ is R25.37, while the current minimum electricity cost with $\alpha = 0.1$ is R18.80, a cost reduction of more than 25%. It is emphasized

Table 3.3: The baseline and optimal appliance commitment status.

No.	Appliance	u^{bl} and u^{opt}	
1	Stove	$u^{bl}_{1,t}$	$t_{37} - t_{39}$, $t_{108} - t_{112}$
		$u^{opt}_{1,t}$	$t_{37} - t_{39}$, $t_{102} - t_{106}$
2	Microwave	$u^{bl}_{2,t}$	t_{108}
		$u^{opt}_{2,t}$	t_{104}
3	Kettle	$u^{bl}_{3,t}$	t_{39}, t_{109}
		$u^{opt}_{3,t}$	t_{39}, t_{113}
4	Toaster	$u^{bl}_{4,t}$	t_{31}
		$u^{opt}_{4,t}$	t_{31}
5	Iron	$u^{bl}_{5,t}$	$t_{108} - t_{112}$
		$u^{opt}_{5,t}$	$t_{97} - t_{101}$
6	Vacuum cleaner	$u^{bl}_{6,t}$	$t_{54} - t_{56}$
		$u^{opt}_{6,t}$	$t_{54} - t_{56}$
7	EWH	$u^{bl}_{7,t}$	$t_{25} - t_{36}$, $t_{105} - t_{116}$
		$u^{opt}_{7,t}$	$t_{25} - t_{36}$, $t_{103} - t_{112}$,t_{121}, t_{122}
8	Dishwasher	$u^{bl}_{8,t}$	$t_{119} - t_{133}$
		$u^{opt}_{8,t}$	$t_{121} - t_{135}$
9	Washing machine	$u^{bl}_{9,t}$	$t_{111} - t_{115}$
		$u^{opt}_{9,t}$	$t_{97} - t_{101}$
10	Tumble dryer	$u^{bl}_{10,t}$	$t_{120} - t_{122}$
		$u^{opt}_{10,t}$	$t_{118} - t_{120}$

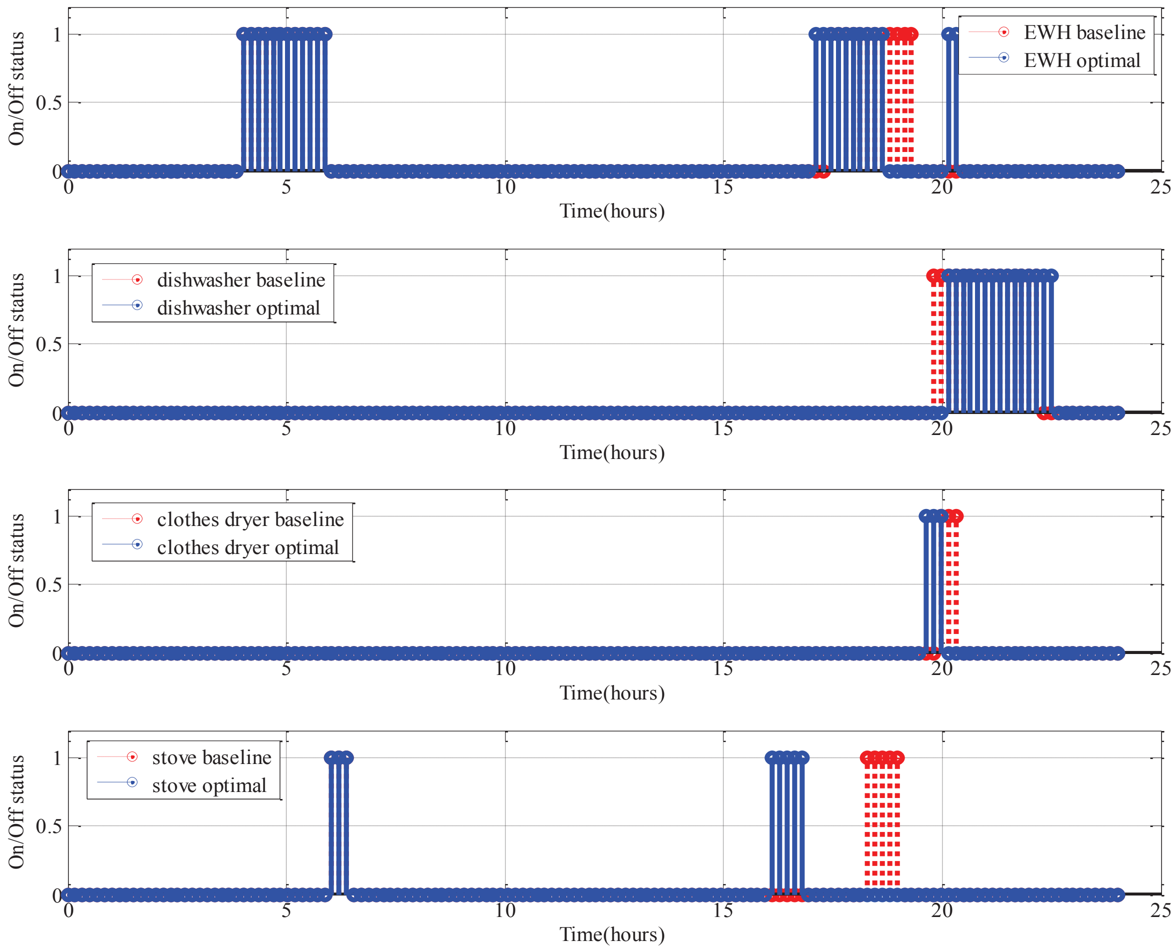

Figure 3.1: The baseline and optimal switching status of high cost appliances

that the amount of savings realized cannot be generalized because the amount of savings may be affected by the price disparity between peak and off-peak prices; in our case off-peak price is more than 30% of the peak price. The value realized can also be affected by the amount by which appliances can be shifted. The results show that the appliances are generally shiftable and this is because of the range that the consumer provided or their level of flexibility. The results also show an earned incentive of R1.87. Figure 3.2 shows that the consumer's morning peak remained relatively the same at 4.5kWh $t = 34(05:40)$. The evening peak of 10.5kWh has been shifted from peak time $t = 113(18:50)$ to off peak time $t = 97(16:10)$ at a lower value of 8.4kWh due to load redistribution. This redistribution of the load can assist the stressed power system at peak times. The schedule inconvenience defined by (3.6) at $\alpha = 0.1$ is 57.

Table 3.4 shows the solution of the sensitivity analysis of parameter, inconvenience weighting

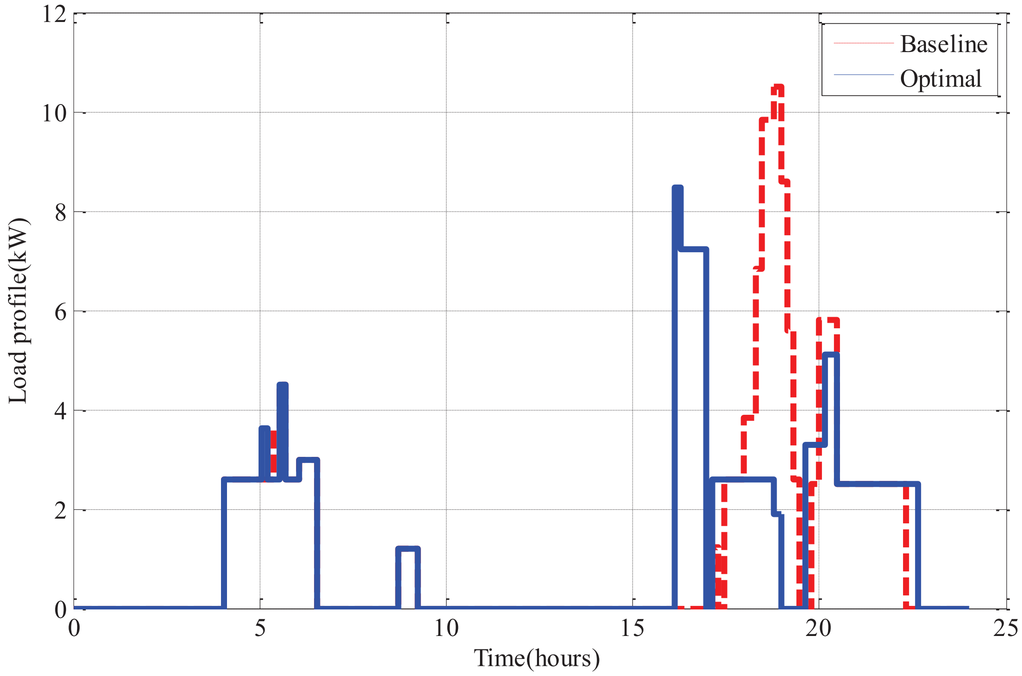

Figure 3.2: The load profile under both baseline and optimal schedule.

factor on the daily cost (J_c) and the inconvenience (I). A different weighting factor reflects the consumer's different preferences regarding financial cost and inconvenience. The high value of alpha means a high penalty on inconvenience and the cost will assume a highest value and smallest value of inconvenience. This is in agreement with (3.7), because α is a tradeoff between the inconvenience and the cost. The weighting factor of appliances can be made to vary between appliances; however for simplicity the authors have assumed a uniform weighting factor. It is also to be noted that the selection of the proper value of α is subjective, as it is dependent on the user's preference. The different values are only a guide to the consumer. In addition, in Table 3.3 the value of J_c reaches a ceiling of R24.995, which is commensurate with constraint (3.2), that the consumer is willing to spend not more than R25 on that day. The weighting factor of 0 means the consumer's decision is not influenced by the inconvenience and at that time the inconvenience assumes the highest value of 73, while the cost is at its lowest value of R12.87. The higher values of α mean high importance is placed on the inconvenience, for example at α=100, J_c is highest at 24.995 and the inconvenience is the smallest value of 3. This tradeoff between cost and inconvenience can help consumers in making a choice on how much they are willing to be inconvenienced, which may affect the level of participation in the program.

Table 3.4: Energy and inconvenience costs at different weighting factors.

α (R)	Total cost (J_c)(R)	Inconvenience (I)
0	12.87	73
0.5	20.800	29
1	22.661	17
10	24.786	7
25	24.995	3
50	24.995	3
100	24.995	3

3.4.1 Further discussions

The optimal solution obtained is a suggestion to the consumer on cost minimization against the inconvenience that comes with the new schedule. Once the optimal solution is obtained, the reasonability of the optimal solution is analyzed. It is noted that the amount of savings realized is comparatively high and cannot be generalized because the savings may be affected by the price disparity between peak and off-peak prices; in our case off-peak price is 31.5% of the peak price. The value realized is also affected by the amount at which appliances are shifted. In this case study, all appliances were flexible within certain time ranges that were specified by the consumer, hence the the relatively higher savings whereas the expectation was that these would be lower when some appliances were considered inflexible. Future work will consider households on a larger scale rather than one household. In addition, future studies will consideration of storage system and photovoltaic generator as well as carbon emissions saved. This will assist in determining the consumer's energy cost, energy savings as well carbon emissions mitigation. It is believed that if the consumer has all these knowledge options, more energy could be saved that could reduce peak consumption and stabilise the power system. This study also could motivate the consumer's awareness on how much they could reduce the environmental impact through knowledge of clean energy technologies.

Based on our work there is a possible future smart phone application for offering actional information to end users that could be based on our optimization back end work with alpha as the use-selected parameter of various levels of inconvenience. It is anticipated that when this level is too high, that means ”sacrifice” so a nonlinear incentive curve should be considered or recommended.

3.5 CHAPTER SUMMARY AND CONCLUSION

The chapter gives preliminary results from a study using a formulated MINLP optimal control model. A typical case study on a single household in South Africa has been carefully studied. The study in this chapter provides two results; one on load shifting and curtailment, and the other is on the effect of weighting factor on both the cost and inconvenience.

The study show that consumers reschedule their appliances through load shifting to lower priced periods due to variable electricity prices from the price based demand response pricing strategy of TOU tariff. It is also shown that an incentive offered during peak times can cause load curtailment during those times in order for the consumer to benefit from incentive prices. The consumer reduces the cost of electricity by more than 25% and also earned some incentives. It is noted that the amount of savings realized cannot be generalized because the savings may be affected by a number of factors, such as shiftable appliances and a price difference between peak and off-peak times. Because of load shifting, the utility could benefit from levelized load consumption on maintaining power system network stability.

Inconvenience level that measures the disparity between the proposed appliance schedule against the baseline appliance switching status obtained from on site measurements has also been studied and it is shown that at different values of the weighting factor α, the inconvenience coefficient, the consumer has varying costs. From these results, the consumer is able to know the inconvenience level that comes with the new schedule and be able to adjust it according to his preferences relative to the cost. Therefore a final decision concerning participation in the program could be made.

CHAPTER 4

OPTIMAL SCHEDULING OF HOUSEHOLD APPLIANCES WITH BATTERY STORAGE AND COORDINATION

4.1 CHAPTER OVERVIEW

This chapter follows and improves on the foregoing chapter with these two aspects; the mathematical model formulation considers the effect of appliance coordination and also incorporates a battery storage system under time of use electricity tariff. This chapter is also based on our published work that bears the same title [28]. Baseline power consumption measurements of individual appliances considered were performed and demand profiles are graphically presented. In this work, a mixed integer nonlinear programming mathematical model with more practical operation constraints for appliance coordination and battery scheduling is formulated and solved. The simulation results show effectiveness of the algorithm in that by optimally scheduling appliances and battery storage system, cost saving, peak shaving and valley filling are achieved through load shifting. The energy cost saving that might be beneficial to consumers; and peak shaving and valley filling, which are of great importance to the utility. It is found that consideration of appliance coordination yields smaller cost saving because of interdependent operation. Without the battery and coordination, a cost saving of 22% and peak reduction from 10.355 kW to 8.405 kW are realized. Consideration of appliance coordination gives a further cost saving of 1% and a relatively smaller peak reduction to 8.30 kW. The battery bank system promotes peak shaving and valley filling and a further cost saving of about 6% and peak reduction to 5.175 kW. Sensitivity analysis, however, reveals that the energy cost saving is sensitive to the consumer's willingness to pay. This analysis has not been performed in any of the literature in this area.

The remainder of this chapter is organized as follows: Section 4.3 focuses on defining the problem and section 4.4. presents optimization model formulations. Section 4.5 provides information on the data used in this chapter. The solution methodology is presented in section 4.6 and measured, simulation results are presented and discussed in Section 4.7 and lastly a conclusion is presented in section 4.8.

4.2 PROBLEM DEFINITION

The layout of the problem is shown in Figure 4.1. The energy flows are indicated by the arrows. The reader will notice that the battery bank consumes power from the mains. This will happen during off-peak times, while it feeds the load during peak times.

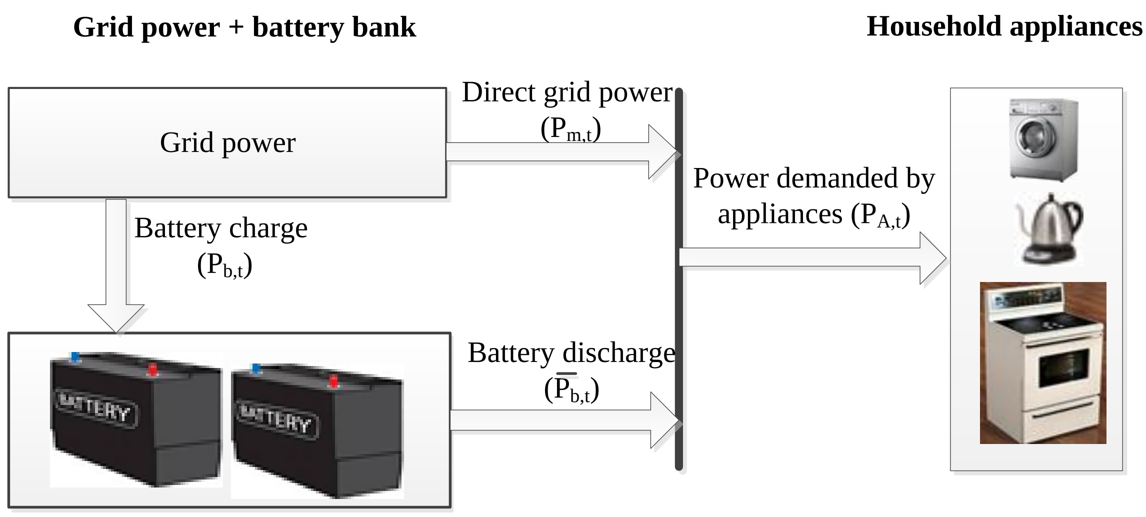

Figure 4.1: Layout of the presented problem

The optimal control problem of household appliance scheduling with storage entails control inputs as the energy demand, the desired time of starting and completing tasks, appliance rated power, the baseline schedule, TOU tariff, battery input and output efficiencies, as well as capacity. The control decisions are the scheduling status of appliances, power flows from the grid and battery state of charge (SOC), which has battery charging and discharging power as control variables. The main objective is to determine the minimum cost of scheduling these appliances, taking into account the necessary constraints and inconvenience level. This problem is of great importance because worldwide research on DR, of which the main purpose is to reduce energy consumption, particularly during peak times, has opened new possibilities for advanced planning and control of supply and demand, especially at residential level where appliance scheduling plays a major role. A major benefit of appliance scheduling is that home-owners can compare the cost benefit among different inconvenience levels that come with an optimal solution against the baseline schedule [25].

4.3 MATHEMATICAL MODEL FORMULATIONS

In this section, we formulate the mathematical model as an MINLP optimization problem for the household appliance scheduling problem with a battery as storage device. First we present the energy cost model, then the battery model and finally we formulate the problem's objective function, incorporating the battery and scheduling inconvenience.

An electricity-consuming household's objective is to minimize its electricity cost during a dynamic price tariff. The current work is an improvement of our previous work [25] and those of [26, 68, 71] in that a number of practical operational constraints have been incorporated and the battery has been considered.

$$J_e = \sum_{t=1}^{T} \sum_{i=1}^{A} P_i \Delta t \rho_t u_{i,t}, \tag{4.1}$$

$$P_i > 0, \rho_t > 0, i = 1, ..., A, t = 1, ..., T,$$

$$u_{i,t} = \begin{cases} 1, & \text{when appliance } i \text{ is on at } t; \\ 0, & \text{when appliance } i \text{ is off at } t, \end{cases}$$

where J_e is the appliances' energy cost function appliances, an index of appliances $i \in A$ (a set of appliances), $t \in T$, $\Delta t = 10$ minutes, ρ_t is the electricity price and $u_{i,t}$ is the appliances commitment status. In a household scheduling problem there are three main types of constraints: appliance operation time, continuous operation and maximum cost or maximum energy constraint. Additional constraints can be added, such as; coordination, inconvenience and comfort constraints, if there are any [68,97]. The following constraints are formulated to the objective function (4.1):

a) Maximum cost

$$\sum_{t=1}^{T}\sum_{i=1}^{A}(P_i u_{i,t} + P_{b,t})\rho_t \Delta t \leq C. \tag{4.2}$$

This constraint models the maximum cost that the consumer is willing to incur within the control horizon. The parameter C is obtained from the consumer's bill and $P_{b,t}$ is the battery's charging power as elaborated further in section 4.3.0.1.

b) Appliance operation time

Given the predetermined parameters d_i, e_i and N_i, as the start, end time of operation and the allowable operation duration; to provide the needed consumption for each appliance, in times within interval [d_i,e_i] it is required that,

$$\sum_{t=d_i}^{e_i} u_{i,t} = N_i + k_i, \forall i, \tag{4.3}$$

where $N_i \leq (e_i - d_i)$ and $k_i \in \mathbb{Z}$ is the additional run time of appliance i. Note that this constraint has been modified from the standard one that appears in [25, 26, 68, 71]. It now offers flexibility to consumers in that they can choose to increase or reduce the run time wherever possible. For example, if the estimated cooking time is 50 minutes, the consumer can choose to increase or reduce it by k_i.

c) Appliance continuous operation

This constraint ensures continuous operation of appliances. The importance of this constraint is that it avoids interruption of appliance operation [96].

$$\sum_{t=d_i}^{e_i} u_{i,t} \cdot u_{i,t+1} \cdot u_{i,t+2} \cdots u_{i,t+(N_i-1)} = 1. \tag{4.4}$$

d) Appliance coordination

Coordination between household appliance commitment is very important because some household appliances are committed relative to others, that is, operating one appliance may necessitate operation of the other at the same or at a delayed time. The following algebraic constraint examples are used to model appliance coordination and reference is made to Table 4.1 for clarity.

Inequality (4.5) could be applied to an appliance with sequential operational tasks where the first task cannot be performed concurrently with the second one. This constraint is also applied to appliances that are not to be committed at the same time. An example from a set of laundry appliances would be a washer/dryer combination machine; the washing (with index $i = 10$) cannot be done at the same time as drying ($i = 11$).

$$u_{10,t} + u_{11,t} \leq 1, t = 1, ..., T. \tag{4.5}$$

The following inequality is necessary to ensure that, for example, the dryer follows the washing machine:

$$d_{10} + N_{10} \leq d_{11}. \tag{4.6}$$

If two appliances are on at the same time, such as the television ($i = 12$) and the decoder ($i = 14$), then the equality is modeled as,

$$u_{12,t} - u_{14,t} = 0, t = 1, ..., T. \tag{4.7}$$

If one appliance is off while the other is on, this is represented by the inequality constraint (11). An example would be a DVD player and a decoder. The DVD player ($i = 13$) is off when the decoder is on with the same television set. This is represented by;

$$u_{13,t} + u_{14,t} \geq 1, t = 1, ..., T. \tag{4.8}$$

An example of a television being off, then the DVD player is off, is represented by (4.9). Another example would be television room lights being switched off when the television is off.

$$u_{13,t} = 0 \quad \text{if} \quad u_{12,t} = 0. \tag{4.9}$$

To coordinate the lighting with the appliances used in their respective rooms, we use constraint (4.10). With reference to the laundry room, as indicated in Table 1; the only time the laundry lights are off is if neither the washing machine nor the dryer is on.

$$u_{3,t} = \begin{cases} 1, & \text{if} \quad u_{10,t} \quad \text{or} \quad u_{11,t} = 1, \\ & \text{or} \quad u_{10,t} = u_{11,t} = 1, \\ 0, & \text{if} \quad u_{10,t} = u_{11,t} = 0. \end{cases} \tag{4.10}$$

e) Appliance power consumption limits

$$0 \leq P_{i,t} \leq P_i^{max}. \tag{4.11}$$

4.3.0.1 Battery model

In our current work it is assumed that the household under study has a battery bank as a storage device. The BESS is characterized by continuous charging and discharging power, therefore $P_{b,t}$ and $\bar{P}_{b,t}$ are considered continuous variables. The general battery dynamics are presented by the battery's state of charge (SOC) [98, 99];

$$E_t = E_0 + \eta_c \sum_{\gamma=1}^{t} P_{b,\gamma} \Delta t - \eta_d \sum_{\gamma=1}^{t} \bar{P}_{b,\gamma} \Delta t, 1 \leq t \leq T, \tag{4.12}$$

where E_t is the SOC of the battery, E_0 is the initial SOC, whereas $\eta_c \sum_{\gamma=1}^{t} P_{b,\gamma} \Delta t$ is the battery energy during the charging period and $\eta_d \sum_{\gamma=1}^{t} \bar{P}_{b,\gamma} \Delta t$ is the battery energy during the discharge period. Note that at a time when the battery is consuming power, it is treated as an appliance, whereas during discharging it acts as a source. η_c and η_d are the battery's charging and discharging efficiencies. The objective is to minimize the cost of charging and maximize the cost of discharging the battery. Therefore the cost objective function for the battery is as follows:

$$J_b = \sum_{t=1}^{T} P_{b,t} \rho_t \Delta t, \tag{4.13}$$

with continuous control variables $P_{b,t}$ being the battery power during the charging period.

a) Battery energy capacity limits

The battery capacity limits provide the upper and lower bounds to the battery capacity.

$$E^{min} \leq E_t \leq E^{max}, t = 1, ..., T, \tag{4.14}$$

where E^{min} and E^{max} are related through depth of discharge (DOD) as follows;

$$E^{min} = (1 - DOD)E^{max}. \tag{4.15}$$

b) Avoiding charging while discharging

We consider that battery charging and discharging operations are mutually exclusive. Therefore the battery cannot charge and discharge at the same time; the constraint below is applied. This constraint also allows the state of the battery to be idle while it is not charging or discharging.

$$P_{b,t}.\bar{P}_{b,t} = 0; \tag{4.16}$$

c) System power balance

The power demanded by the load at time t should be met by both the discharging battery and the mains supply;

$$\bar{P}_{b,t} + P_{m,t} = P_{D,t}, \tag{4.17}$$

where

$$0 \leq P_{m,t} \leq P_m^{max}.$$

$\bar{P}_{b,t}$ is the battery power during discharge, $P_{m,t}$ is the power from the grid and $P_{D,t}$ is the aggregated power demanded by the appliances together with the battery at time t. Without the battery, the power supplied by the grid is equivalent to the power consumed by the aggregated household load, $P_{m,t} = P_{D,t}$. Aggregated power consumed by appliances excluding the battery is;

$$P_{A,t} = \sum_{i=1}^{A} P_i u_{i,t}, \tag{4.18}$$

while the aggregated consumption of the appliances and the battery is given by:

$$P_{D,t} = P_{A,t} + P_{b,t}. \tag{4.19}$$

The total power consumption of appliances under consideration and the battery, P_D in a day is given by:

$$P_D = \sum_{t=1}^{T} (P_{A,t} + P_{b,t}). \tag{4.20}$$

4.3.0.2 The inconvenience level

The purpose of the scheduling inconvenience (I) is to minimize the variation between the baseline and the optimal schedule [25]. The consumer therefore also minimizes the inconvenience given by:

$$I := \sum_{t=1}^{T} \sum_{i=1}^{A} (u_{i,t}^{bl} - u_{i,t})^2. \tag{4.21}$$

The baseline $u_{i,t}^{bl}$ is obtained from the measured results as shown in Table 4.1.

4.3.1 The overall objective

The inconvenience cost and the battery sub-objectives are incorporated in the main objective, therefore the final objective function that the consumer desires to minimize is expressed as follows:

$$J = (J_e + J_b) + \alpha I \Delta t, \tag{4.22}$$

where J_e is the energy cost function as in (4.1) and J_b is the battery energy cost function as shown in (4.13). It is to be noted that the inconvenience as presented in (4.21) is a unit less value. Therefore to express all sub-functions within the overall objective function (4.22) with the same unit, there is a need to use some form of cost coefficient to express all sub-functions in the same units. In this work we use the tariff $\alpha = \rho(t)$ as an assumption. In the previous chapter we had assumed the parameter $\alpha = 0.5$ and a sensitivity of this parameter has been tested on the same chapter which was shown to affect the solution. The assumption in the current chapter however, assumes that the consumer is paid the equivalent amount to the electricity charge on their inconvenience. To date, determining the cost coefficient that will work both for the utilities and consumers remain one of the research gaps in this study.

The model obtained in (4.1)-(4.22) is the MINLP model with control variables $u_{i,t}$, $P_{b,t}$, $\bar{P}_{b,t}$ and $P_{m,t}$.

4.4 MODEL PARAMETERS

A typical household in South Africa is used as a case study. Fourteen appliances are selected and studied and results are shown in Table 4.1. Field measurements are conducted to obtain baseline commitment and the profile of appliances under consideration. Appliance rated power is specified by the appliance manufacturers and can be obtained from the appliances. Data on appliance usage in the household under study were collected, as well as information on the allowable time duration required to finish the normal operation of the appliance, N_i. The information on d_i and e_i as the beginning and end of the time interval in which the appliance is scheduled is specified by the user, based on the usual or preferred usage. This is shown in the last column of Table 4.1 where, for example appliance 4, $d_i = 115$ $(19:10)$ and $e_i = 129$ $(21:30)$ are the average time ranges at which the appliance is normally switched on. This is typical of a working class household where most activities occur in the morning and after work. Appliances considered are shown with their rated power and normal operation time ranges. The baseline on appliance operation time is also shown.

The tariff structure used is based on South Africa's TOU Homeflex 1 for household consumers. The Homeflex 1 tariff has five charge components as service charge, transmission network charge, environmental levy, peak and off-peak charges[1]. We model these into fixed and variable charges as follows:

Table 4.1: Appliances data

No.	Appliance	Rated power P_i (kW)	Run-time N_i,(mins)	Baseline Avg. (Hrs) $u_{i,t}^{bl}$ d_i-e_i
	Lights			
1	Kitchen	0.011		As kitchen appliances
2	TV room	0.011		As TV
3	Laundry room	0.011		As laundry appliances
	Kitchen			
4	Dishwasher	1.8	150	115-129
5	Breadmaker	1.5	150	117-131
6	Stove	2.0	30, 50	31-33, 112-116
	swimming pool			
7	1Hp pump	0.75	120	103-114
	Heating			
8	Space heating	2.4	120	108-119
9	EWH	3.0	120,120	30-41,103-114
	Laundry			
10	Washing machine	2.0	60	108-113
11	Clothes dryer	2.0	30	115-117
	Entertainment			
12	Television	0.133	180	103-120
13	DVD player	0.025	180	103-120
14	Decoder	0.07	180	103-120

Table 4.2: Battery data

Battery capacity	10kWh
η_c	75%
η_d	100%
DOD	50%

$$\rho_t = F_C + V_C,$$

where F_C is a fixed charge and consist of service charge, network charge and environmental levy, while V_C are peak and off-peak energy charges.

$$F_C = R(2.96 + 3.68 + 2.00)/100,$$

and

$$V_C = \begin{cases} R1.7487, & \text{peak time, } t \in [07{:}00,10{:}00),[18{:}00,20{:}00); \\ R0.5510, & \text{off-peak time, } t \in [00{:}00,07{:}00),[10{:}00,18{:}00],[20{:}00,00{:}00]. \end{cases}$$

The household under consideration is assumed to have a battery bank, which is the most standard device used to store energy because of their relatively low price, relatively low investment cost, high availability, reasonable performance and life characteristics [98]. Most literature states that the lead acid battery has a discharge efficiency of 100%, whereas the charging efficiency is in the range of 65-85% [87, 98, 99]. A point to note about the battery is that for it to work with an AC network, there has to be conversion and inversion from AC to DC and DC to AC. It is acknowledged that there are some losses within these electronic modules. However, for our work the net efficiency has been used, that is, converter/battery as charging efficiency and battery/inverter as discharging efficiency. Therefore the battery data used are shown in Table 4.2. The minimum discharge capacity of 50% has been shown to sustain the lifespan of the battery [98].

Other data shown in Table 4.3 are the maximum cost that the consumer is willing to incur or the consumer's budget. This value is obtained from the consumer's bill. The maximum power from the grid has an assumed power factor of 0.75. It is assumed that the appliances

Table 4.3: Other data

Daily maximum bill (C)	R25
Maximum power from the mains(P_m^{max})	$230V * 60A * 0.75 * 0.5 = 5.2kW$

considered can consume a maximum of 50% of the household maximum power at any time t.

A point to note on battery cost is that it entails capital cost, operational and maintenance (O&M) costs. Since our study horizon is one day, we only consider $O\&M$ costs. However, the impact of investment cost cannot be ignored during longer study periods [100–102]. In [103–105], the $O\&M$ cost of a lead acid battery has been estimated to a specific annual value or some online sources estimate the annual $O\&M$ cost to be less than or equal to 2% of capital cost. In this work, our estimate is guided by [103–105] that use a fixed value of 22 EUR/kW/year and we convert to a daily equivalent of R 0.8178kW/day.

4.5 SOLUTION METHODOLOGY

Field measurements were conducted to obtain the baseline commitment and the profile of appliances under consideration. During these measurements the TOU tariff was used. The MINLP optimization problem (4.1)-(4.22) is solved with an optimization solver, SCIP, available in the Matlab interface OPTI toolbox. SCIP is currently one of the fastest non-commercial solvers for MIP and MINLP. It is also a framework for constraint integer programming and branch-cut-and-price[20,21]. It uses Interior Point Optimizer (IPOPT) and SoPlex as nonlinear and integer algorithms. SoPlex is an advanced implementation of the revised simplex algorithm for solving linear programs. It features preprocessing, exploits sparsity, and provides primal and dual solving routines. It is the default LP solver in SCIP. IPOPT implements an interior-point line-search filter method[17,22] [106, 107] The solver offers solutions to problems of the form:

[20]SCIP: Solving Constraint Integer Programs.< http://scip.zib.de/>.

[21]T. Berthold, et al., Solving mixed integer linear and nonlinear problems using the SCIP Optimization Suite, ZIB-Report 12-27 (July 2012), TakustraÃ§e 7 D-14195 Berlin-Dahlem Germany. <file:///C:/Users/User/Downloads/ZR-12-27%20(1).pdf>

[22]Opti Toolbox solvers. <http://www.i2c2.aut.ac.nz/Wiki/OPTI/index.php/Solvers>

$$\min f(x), s.t., \begin{cases} Ax \leq b, A_{eq}x = b_{eq}(\text{linear constraints}) \\ c(x) \leq d, c_{eq}(x) = d_{eq}(\text{nonlinear constraints}) \\ Lb \leq x \leq Ub(\text{variable bounds}) \\ x_i \in \mathbb{Z}(\text{integer decision variables}) \\ x_j \in \{0,1\}, i \neq j(\text{binary decision variables}) \end{cases}$$

The measured results are compared with simulation results to demonstrate the effectiveness of the algorithm.

4.6 MEASURED, SIMULATION RESULTS AND DISCUSSIONS

The consumption of the appliances considered for one household is monitored using an Efergy E2 Classic energy monitor. The Efergy E2 Classic is a wireless electricity monitor that allows monitoring of electrical energy consumption trends over time in households. It includes an innovative software package that allows tracking energy usage on a computer. The measuring device has three components, as shown in Figure 4.2, and a typical connection is shown in Figure 4.3.

Figure 4.2: Efergy E2 classic energy monitor components

Figure 4.3: Connection at the DB

Sensor unit: This component is hooked onto the electricity meter's incoming supply cable for aggregated household energy measurement but for individual appliance measurements, it is connected to the live wire of the appliance three-core cable. This excludes the electric water heater (EWH), which is supplied directly at the distribution board (DB); hence its measurements are made at the DB. *Transmitter unit:* The purpose of the transmitter is to link the sensor cable to the display unit through transmission of measured data. This component captures data at least every 6 seconds. *Display unit:* The function of the unit is to display energy usage information and demand profile and the cost of energy being consumed. The numerical hourly average data are provided for analysis. This device is kept at a distance of not more than 70m from the transmitter unit[21].

The Efergy E2 Classic monitor has been shown to have 2% error[22], which makes the results reliable. South Africa's residential load management (RLM) program, which enables the municipal control of residential EWH, necessitates that the EWH be supplied differently from other household appliances for ease of external control[23]. This residential unit is located in a

[21] < http://www.sustainable.co.za/efergy-e2-optical-wireless-electricity-monitor.html>.
[22] < http://efergy.com/manuals/e2classic_instructions_web2011.pdf>.
[23] R.S. Pandaram, Residential load management (RLM) in South Africa: challenges and solutions.

block of houses where the EWH control devices are located at a localized meter box, hence the invisibility in the DB. Typical profiles of two appliances are shown in the figures below. These are for the stove and the EWH. The aggregated profile for the appliances considered is shown as the baseline profile in Figure 4.6.

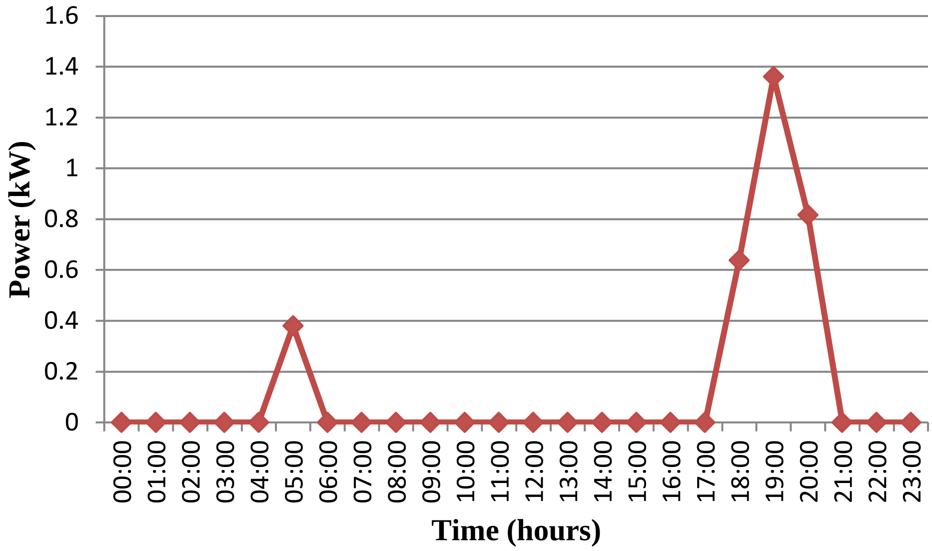

Figure 4.4: Demand profile for the stove

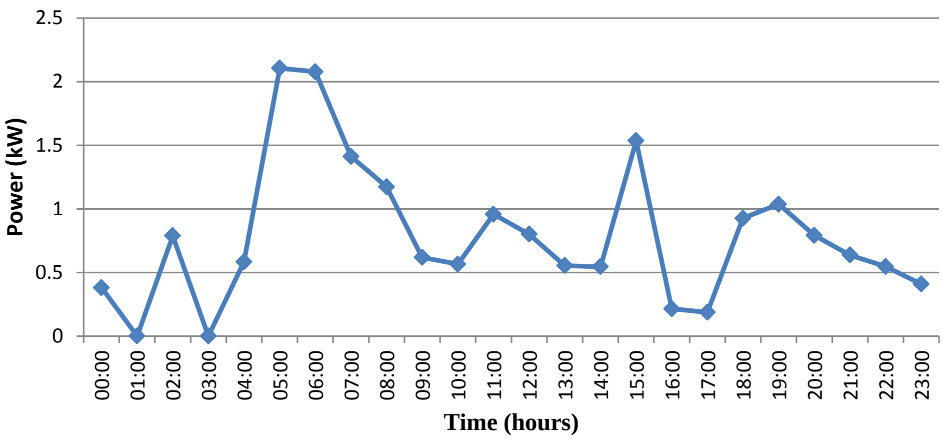

Figure 4.5: Demand profile for the EWH

Since the occupants of the house are working class people and consumption that occurs at night and during daytime when the occupants are not around or not active, it is the opinion of the writers that the consumption is due to the EWH standby losses[24]. It is clearly seen,

<http://active.cput.ac.za/energy/past_papers/DUE/Pandaram.pdf>.

[24] Q. Caherine, J. Wheeler, R. Wilkinson, G. De Jager, Hot water usage profiling to improve geyser efficiency. <http://www.erc.uct.ac.za/23-jesa-catherine-etal.pdf>

particularly in the evening, for both the stove and EWH that the consumption is during peak times between 18:00 and 20:00. One of the challenges of using this measuring device is that the cost comparison can only be made at monthly level.

The measured baseline cost of the EWH=R 11.82 and stove=R 6.0629 for the profiles shown in Figures 4.4 and 4.5 and the TOU tariff as in section 4.2. The effectiveness of the algorithm is demonstrated in the results obtained from our simulation results. The optimization solution with the TOU tariff shows a shift in the consumption profile of appliances. Because of load shifting, for example, the EWH shows one day's cost of R 8.33. This shows a cost saving for this appliance of 29.5%. The stove shows R 4.70; this gives a cost saving of 22.48%. It is to be noted that our simulation results may show an over-estimation because, for example, for the stove we assume fixed power consumption whereas in practice the appliance is a heat regulator, hence the actual consumption is variable.

A very interesting observation is derived from Figure 4.5 in that the field measurements show continuous consumption values of EWH. The assumption is made in this thesis that the appliances consume maximum power rating whenever committed because it is very complex to ascertain the actual consumption values and also that the optimization problem is discrete in nature. This observation however, shows that the values reported could be an overestimation. This could also be extended to other appliances such as stove.

The challenge with this meter, however, is that when performing individual appliance measurements, the live wire from a three-core cable has to be exposed in order to monitor the consumption and this may pose safety issues. Another challenge is that the monitoring device can be used to make a cost comparison for one month for different tariffs. Since our study horizon is 24 hours, the daily estimates may not reflect a true cost value for the day in consideration. It is to be noted that for simplicity, in our simulation results we have excluded standby losses.

The simulation results provided are with additional run time $k_i = 0$ and $\alpha = \rho(t)$. In our previous work [25] we tested different values of alpha where it was discovered that the simulation result was sensitive to the value of alpha. The high value of alpha generated the highest cost value and the lowest value of inconvenience. For alpha=0, the consumer's decision is not influenced by the inconvenience and during this time, the inconvenience assumes the highest value, while the cost is at its lowest value. It is to be noted that the selection of the proper value of alpha is subjective, as it is dependent on the user's preference. At this stage we can only make an assumption. In order to differentiate this current work with the previous one, instead of assuming a fixed inconvenience cost coefficient, we now use the TOU tariff, that is $\alpha = \rho(t)$, that is, the consumers opts to go with the utilities' price. The trade-off between the two sub-objective functions of cost and inconvenience can assist consumers in making a choice on the extent they are willing to be inconvenienced, which may affect the level of participation in the DR program.

Figure 4.6 shows simulation results obtained with coordination considered. The appliances' baseline and optimal appliance schedules are shown. The profile shows the baseline and optimal load profiles both with and without battery. It shows that the optimal solution without battery offers shifted consumption and a reduced peak of 8.405 kW t=103, 106 and 107 (17:10, 17:40 and 17:50). The baseline has a peak of 10.355 kW at $t = 112 - 113$ (18:40-18:50). This shows a shifted peak consumption from peak. The energy consumed at peak has also reduced by 18%. The baseline energy cost is R 31.77, while the optimal cost realized without battery is R 24.76, a saving of 22%. This saving is relatively higher compared to most results obtained with the TOU tariff owing to the high disparity between the peak and off-peak Eskom prices; the latter is 30% of the former.

The battery SOC shows that the battery charges during off-peak from $t = 0$ (00:00) to $t = 7$ (01:00) and discharges from $t = 102$ (17:00) to $t = 120$ (20:00). Load profiles 1 as a relation between the baseline and the optimal load profile without a battery is included here for ease of comparison. Load profile 2 shows the load profiles obtained from the model solution with and without the battery. It shows the contribution of the battery in peak shaving and valley filling. The battery reduces the peak to 5.1750 kW (10% reduction) and cost reduction to R 23.28. The utilization of the battery brings about a further cost reduction of 6% due to the battery discharge during peak times to aid the power from the grid. a further saving of 6%.

Consideration of appliances coordination yields relatively smaller cost saving because of operation independence. Without coordination, constraints (4.5)-(5.10) are ignored. Consideration of appliance coordination gives a further cost saving 1% and a relatively smaller peak reduction to 8.305 kW. This shows that the work that excludes coordination constraints may

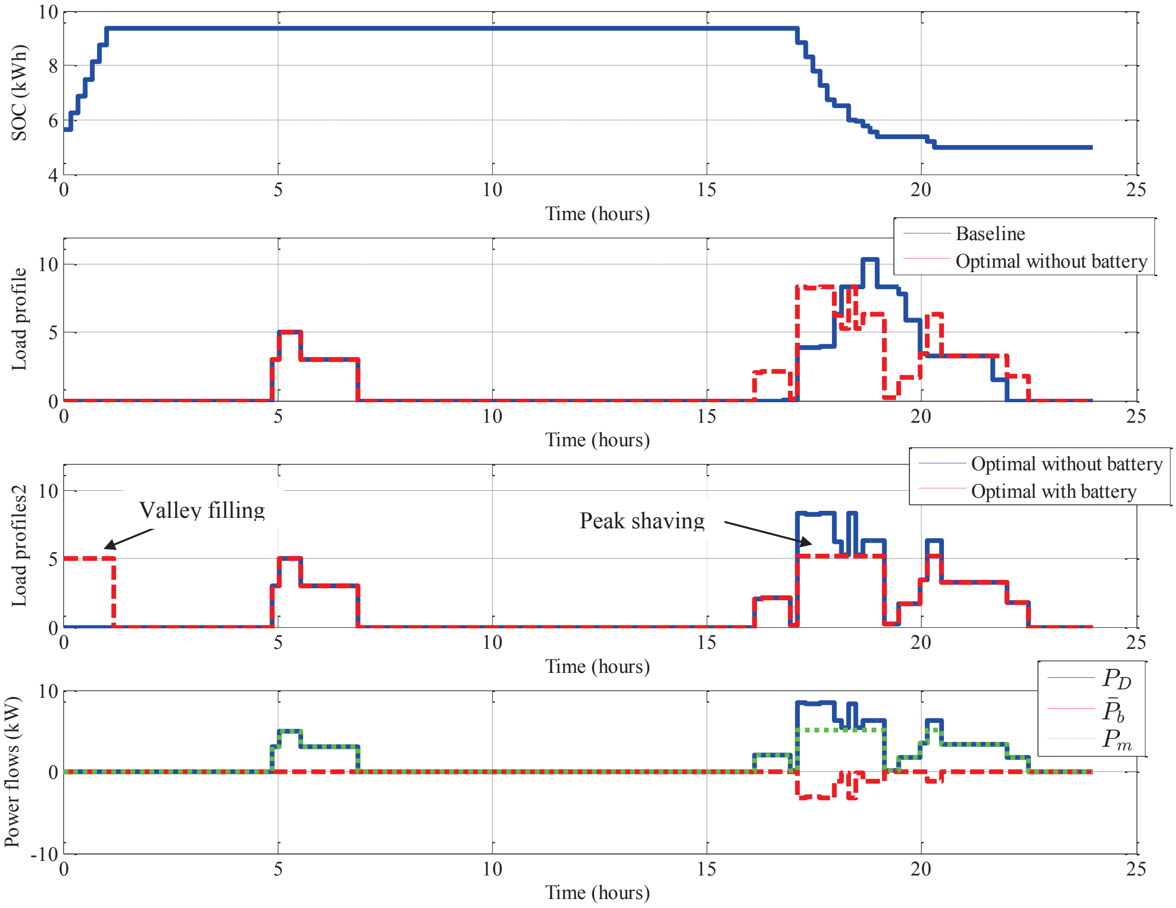

Figure 4.6: Simulation results: Battery state of charge, baseline and optimal load profiles, impact of using battery and system power flows

show inflated residential demand response simulation cost savings.

The figure with power flows shows the power demanded by the load P_D, the power from the grid P_m and the power from the battery $\bar{P}_b$. It is shown that the power demanded by the load is met by both P_m and $\bar{P}_b$, for example at $t = 110$ (18:20), $P_D = 8.305kW$ and this load is met with $P_m = 5.1750kW$ and $\bar{P}_b = 3.13kW$. These power flows satisfy constraint (19).

4.6.1 Illustration of the logic constraints

It is the view of the authors that it is important to present an illustration of the logic constraints (4.9) and (4.10) due to their importance in the problem solution and also that their graphical solution hasn't been presented before. In figure 4.7, the application of constraint

(4.9) to coordinate both the television use to the lights in the room has been met with both appliances getting on and at almost the same time. The television and the lights in the room are both on from 17:00 to 20:00 for a period of 3 hours.

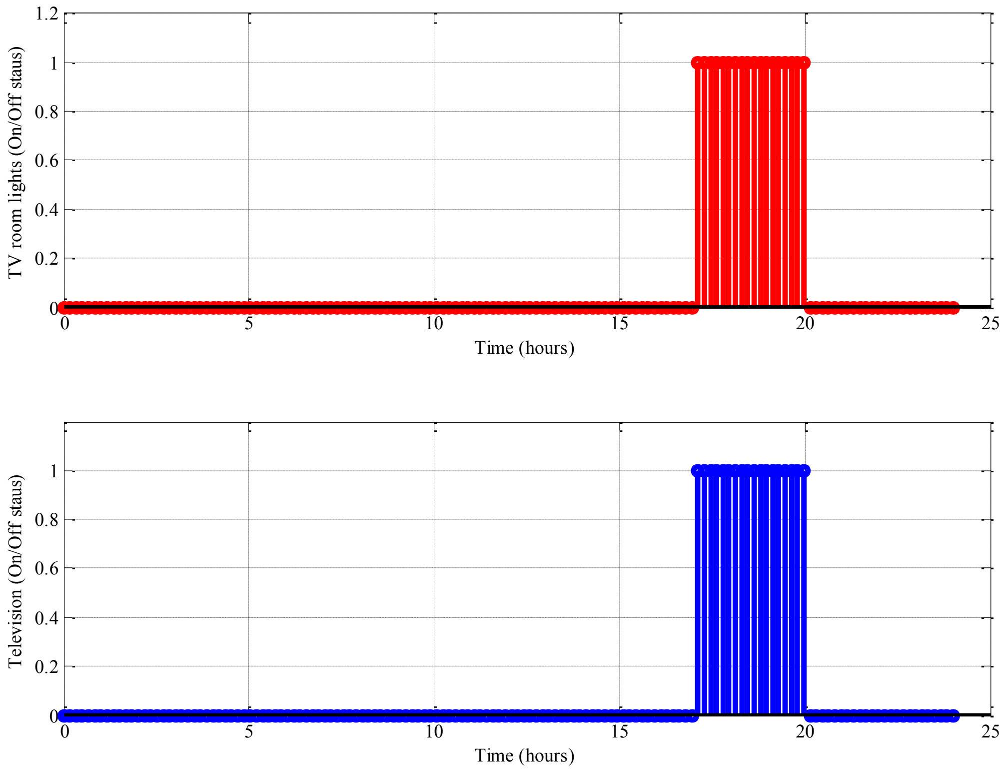

Figure 4.7: Stem results of TV room lights coordinated with television

In figure 4.8 is the illustration of constraint (4.10). It can be seen that commitment of both appliances in the laundry room are coordinated with the lights in that room. However, it is realised that the lights following appliances may cause intermittent use of electricity which may affect the wear and tear of the lights. This as shown in sub-plot three with the lights being off between the operation of appliances. This suggests that the constraint could be improved to show continuous operation of lights tied to the start and finish of the operation of all appliances within a reasonable time, say may be 15 minutes.

4.6.2 Sensitivity analysis of parameter C on the solution.

A sensitivity analysis is carried out to investigate the solution's dependence on parameter C, the consumer's willingness to pay. The results obtained are shown in Table 4.4. We can deduce from these results that the solution obtained is sensitive to how much the consumer is

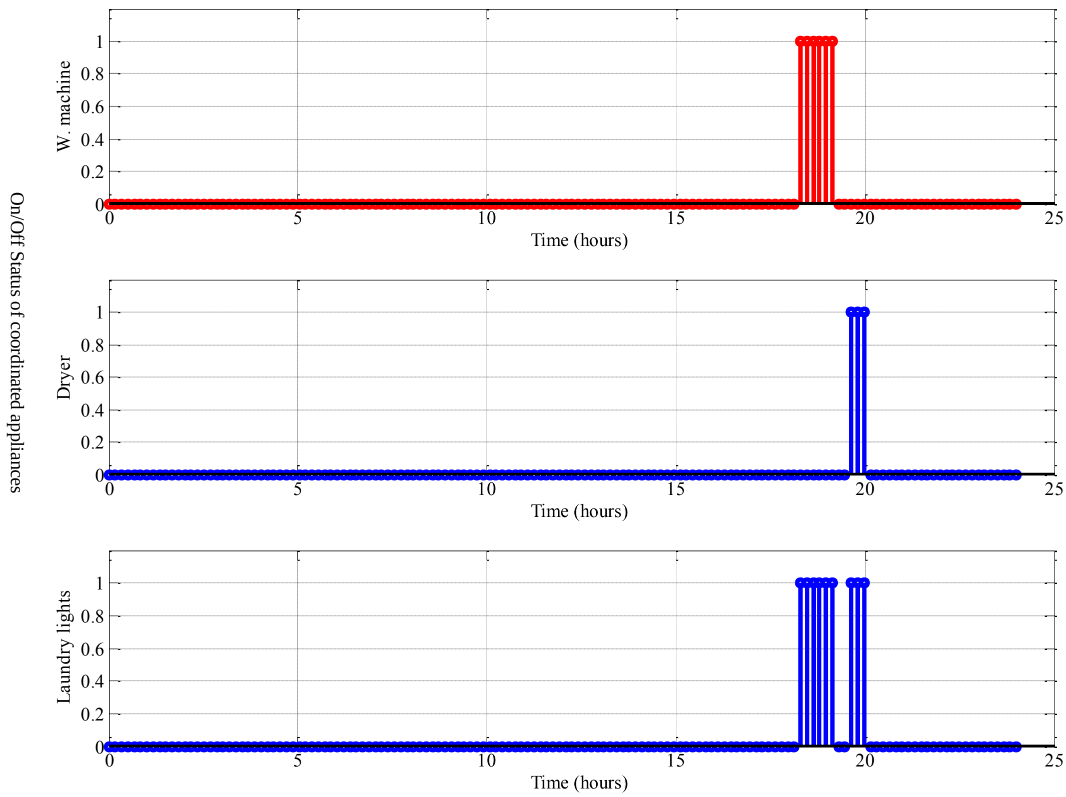

Figure 4.8: Stem results of laundry room lights coordinated with washing machine and dryer

Table 4.4: Sensitivity of parameter C on the results

C (R)	Energy cost, $(J_e + J_b)$ (R)	Energy cost saving (%)	Cost contribution by battery (R)	Inconvenience cost (R)	computational time (sec.)
20	Infeasible				5.59
21	Infeasible				4.98
22	Infeasible				5.13
23	23.0708	27.3779	0.1569	16.1621	5.59
24	23.5728	25.7977	-0.2421	13.8411	6.98
25	24.5189	22.8196	-0.2421	12.5148	7.22
26	25.3298	20.2671	-0.5424	11.1886	7.32
27	25.4425	19.9123	-1.3307	10.5254	7.35
28	26.3096	17.1829	-1.3307	10.0437	7.58
29	27.2731	14.150	-1.3307	9.5620	7.85
30	28.5395	10.1636	-1.1553	9.1709	7.30
40	29.7478	6.3601	-2.1317	8.4796	7.11
50	29.7478	6.3601	-2.1317	8.4796	7.34
100	29.7478	6.3601	-2.1317	8.4796	7.83

willing to spend. When parameter C increases, the energy cost increases, the inconvenience cost decreases, the cost saving decreases while the battery contributes more to cost reduction until solution convergence. These results are commensurate with practical expectation in that if the budget or willingness to pay is less, the minimization algorithm is stringent on the energy cost and the inconvenience cost will henceforth be higher. This, however, shows that the consumer can also use the cost to regulate the algorithm's outcome. Thus in the determination of energy cost saving by the consumer, the amount of savings is affected by the consumer's budget.

4.6.3 Further discussion

The problem presented above is deterministic; one could easily implement the presented model's output as inputs in an open-loop controller. However, because of uncertainty, additional information such as the modelling of the system's stochastic behaviour should be included in order to achieve real time implementation.

In an effort to work towards real time implementation, we are currently working on formulating the model as stochastic to account for uncertain parameters because in practice, the complexity of optimization is brought by the presence of uncertainty brought by some practical system's unknown disturbances. The main challenge of real time implementation is in accurate prediction of the load because of its uncertainty. In this case the uncertainty of the load is practically attributed to both the appliance operation time and power consumption, since they are dependent on; using the stove as an example, such things as the type of event, food, heat regulation, environmental temperatures and even types of cooking devices used. The television may also depend on the day and time of day usage. Comfort level also brings about uncertainty on the load where the consumer may wish to schedule at a different time, hence the need to allow for manual operation. The efficiency of the battery may also be uncertain.

The complexity of dynamic optimization problems makes it hard for general purpose solvers to compute solutions fast enough for a real-time implementation. The simulation package, SCIP we are using is relatively fast with solution time of 7 seconds. SCIP is regarded as one of the fastest non-commercial solvers for MIP and MINLP. However, tailored numerical algorithms may be needed to overcome these challenges in real-time application. Real time implementation require computers that are specifically designed for this purpose, which can be done by faster and more effective tools that offer a platform to integrate software and hardware while capitalizing on the latest computing technologies such as LabView or Matlab combined with DSP.

4.7 CHAPTER SUMMARY AND CONCLUSION

The chapter gives our results from a study using the MINLP household appliance optimization scheduling problem with the necessary constraints and a battery storage.

The optimal results show that consumers reschedule their appliances in response to variable electricity prices, as demonstrated through a TOU tariff. The optimization solution shows consumers can minimize energy cost by transferring their load from peak to off-peak times.

This brings about a cost saving of 22%. Consideration of appliance coordination brings variation in the results obtained. A further energy cost reduction of 6% is achieved by using a battery, which promotes peak shaving as it discharges during peak times. However, since the battery charges during off-peak times, it provides valley filling. This not only affects the net energy cost saving for the household, but also promotes energy balance in the power system, which the utility pursues as a global need. The battery does not bring about a significant improvement when compared with load shifting, which yields a significant energy cost saving because of the charging component of the battery, which has a power consumption cost. Consideration of appliance coordination reduces the cost by a further 1%.

It has been found that the solution obtained is sensitive to input parameter C, the amount the consumer is willing to pay. When C increases the energy cost also increases and the inconvenience cost reduces. This is in line with practical expectations in that if the consumer has a higher budget he is likely to have less inconvenience and high energy consumption cost. This, however, shows that the consumer can also use their budget to regulate the algorithm's outcome.

In the next chapter we consider residential demand response with PV and consideration of carbon emissions savings.

CHAPTER 5

COMBINED RESIDENTIAL DEMAND SIDE MANAGEMENT STRATEGIES WITH COORDINATION AND ECONOMIC ANALYSIS

5.1 CHAPTER OVERVIEW

This chapter improves the preceding chapters by modelling of residential demand response for five households in South Africa instead of one. It is also based on our published work [108] that bears the same title. This study is twofold; the first part proposes an energy management system that combines demand side management strategies with a view of minimizing the consumer's cost and reducing the power consumed from the grid. Appliance scheduling with a dedicated photovoltaic and storage system under time-of-use tariff shows that customers can realize cost savings and the power demanded from the grid is reduced by scheduling power usage optimally. In the second part of this study, we develop a model to investigate the joint influence of price and CO_2 emissions. A similar study has been performed in [109]. However, unlike this reference our study considers not only a battery but also a PV generator. It is found in this study that CO_2 emissions could give customers an environmental motivation to shift loads during peak hours, as it would enable co-optimization of electricity consumption costs and carbon emissions reductions. It is also demonstrated that the consumer's preferences on the cost sub-functions of energy, inconvenience and carbon emissions affects the consumption pattern. These results are important for both the consumer and the electricity suppliers, as they illustrate the optimal decisions that needs to be made in the presence of multiple sub-objectives. Sensitivity analysis, however, reveals that the energy cost saving is sensitive to the consumer's choice of weighting factors. This analysis has not been performed in any of the literature in this area.

The remainder of this chapter is organized as follows: Section 5.3 focuses on the problem definition. Section 5.4 presents optimization model formulations. Section 5.5 provides information on the data used in this study. The solution methodology and simulation results are presented and discussed in Section 5.6 and 5.7 respectively. Section 5.8 presents economical analysis of such a system and lastly a conclusion is presented in section 5.9.

5.2 PROBLEM DEFINITION

We consider set of households H with an index h as shown in Figure 5.1. The households under study are assumed to be connected at a distribution bus P_{bus}. Figure 5.2 shows the power flows in one household with a dedicated PV and storage system.

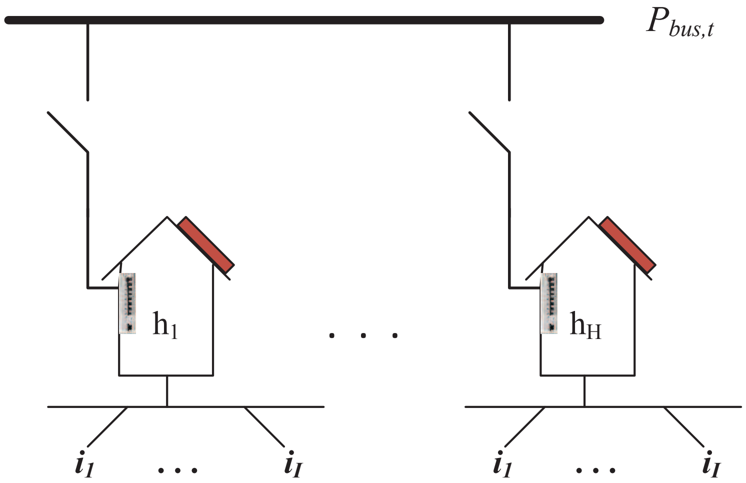

Figure 5.1: Interconnection of the households

The nature of renewable energy sources makes it a challenge to integrate them in a power system. The two primary challenging characteristics of renewable energy sources are their unpredictability and their intermittency. In order to permit integration of renewables into the grid, the voltage and current levels are to follow the grid code that aids proper system synchronization for increased system reliability. The impact of both these challenging characteristics can be mitigated by the application of batteries in the system. Each house has a

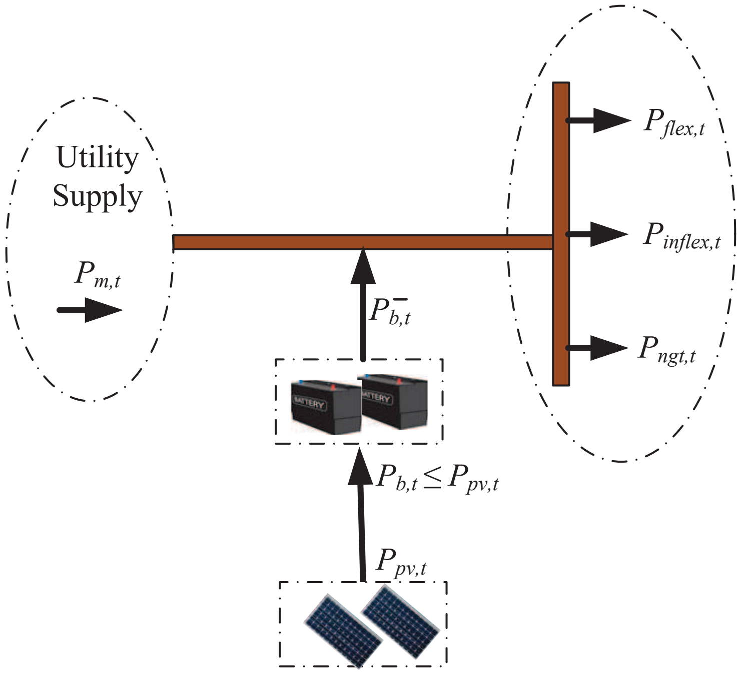

Figure 5.2: Power flows in a household

dedicated PV-battery system and the purpose of the chapter is to formulate an optimal control model that seeks to minimize energy cost, the inconvenience and carbon emissions.

5.3 OPTIMIZATION MODEL

In this section a mathematical model is formulated for the optimal control of the system presented in the previous section. The model formulations are presented as model objective function followed by sub-functions and constraints.

5.3.1 Modeling objective function

A weighting factor method is applied in (5.1) to integrate the sub-objective functions into one. The advantage of this approach is that the consumer has an option to choose the sub-objective to use to control their consumption. Each household seeks to minimize the following combined cost function:

$$\min J = w_1 J_e + w_2 J_I + w_3 J_c \tag{5.1}$$

where w_1, w_2 and w_3 are the weighting attached to these objectives according to the consumer's preference, and $\sum_{j=1}^{3} w_j = 1$. J_e is the energy cost function as in (5.2), J_I is the inconvenience cost function shown in (5.4) while J_c is the carbon emissions cost objective function given in (5.6).

5.3.1.1 Energy cost model

The energy cost objective function (5.2) minimizes the cost of energy consumed by households through optimal scheduling of appliances and the battery using TOU electricity tariff.

$$J_e = \rho_t \Delta t \sum_{h=1}^{H} \sum_{t=1}^{T} (P_{inf,t}^h + P_{ngt,t}^h + P_{flex,t}^h + P_{b,t}^h) \tag{5.2}$$

where

$$P_{flex,t}^h = \sum_{h=1}^{H} \sum_{t=1}^{T} \sum_{k=1}^{K} P_{k,t}^h u_{k,t}^h \tag{5.3}$$

$$P_{k,t}^h \geq 0, \rho_t > 0, k = 1, ...K, t = 1, ..., T, h = 1, ..., H.$$

$$u_{i,t}^h = \begin{cases} 1, & \text{when appliance } i \text{ is on in household } h \text{ at } t; \\ 0, & \text{when appliance } i \text{ is off in household } h \text{ at } t. \end{cases}$$

$P_{inf,t}^h$, $P_{flex,t}^h$ and $P_{ngt,t}^h$ are appliance classifications denoting inflexible, flexible and night-time load, respectively, and each household consists of these three types of loads. Flexible loads can be adjusted according to the consumer's preferences and night-time loads can be committed during the night (22:00-0:500), while inflexible appliances are non-shiftable. k is an index of controllable appliances. $\eta_c \sum_{t=1}^{T} P_{b,t}^h \rho_t \Delta t$ minimizes the cost of charging battery in each household and η_c is the battery's charging efficiency. $u_{i,t}^h$ is the appliance commitment status at time t in household h while $u_{k,t}^h$ is the status of flexible appliance at time t in household h. k is the index of flexible appliances and $k \in K$ where $K \subset A$. $P_{k,t}^h$ is the power consumption of each flexible appliance in time t in household h.

5.3.1.2 Inconvenience cost model

The scheduling inconvenience, I, minimize the disparity between the baseline and the optimal schedule [28]. The consumer therefore also minimizes the inconvenience given by:

$$I_h := \sum_{t=1}^{T}\sum_{k=1}^{K}(u_{k,t}^{bl,h} - u_{k,t}^{h})^2. \tag{5.4}$$

$$J_I = \rho_t \Delta t \sum_{h=1}^{H}\sum_{t=1}^{T}\sum_{i=1}^{K}(u_{k,t}^{bl,h} - u_{k,t}^{h})^2. \tag{5.5}$$

The baseline $u_{k,t}^{bl,h}$ of controllable appliances is obtained from the measured results as explained in data section.

5.3.1.3 Carbon emissions cost model

The carbon emissions model is the carbon footprint of the consumer from the grid electricity usage offset by the injection of emission-free electricity from the PV system. The goal is to minimize the cost of carbon emissions by a household [**?**, 85].

$$J_c = \sum_{h=1}^{H}\sum_{t}^{T}\lambda_C M_{C,t}^{h}\Delta t, \tag{5.6}$$

where J_c is the CO_2 emission cost, λ_C, is the price of CO_2 emission and $M_{C,t}^{h}$ is the mass of emitted CO_2 in kilogram, that is computed as follows;

$$M_{C,t}^{h} = (P_{A,t}^{h} + P_{b,t}^{h} - \bar{P}_{b,t}^{h} - P_{pv,t}^{h})\alpha_{grid}, \tag{5.7}$$

and with the assumption that $P_{b,t}^{h} = P_{pv,t}^{h}$, the equality (5.7) reduces to reduces to (5.8);

$$M_{C,t}^{h} = (P_{A,t}^{h} - \bar{P}_{b,t}^{h}) * \alpha_{grid} \tag{5.8}$$

where α_{grid} is the CO_2 emission rate of the grid, which is 0.99 kg of CO_2/kWh for South Africa's utility,[5] and is charged at $\lambda_C = R0.1323/kg$. $\bar{P}^h_{b,t}$ is the battery's power discharge. Note that the charging of the battery is taken care of by the PV system.

5.3.2 Model constraints

5.3.2.1 Battery model

The PV-battery system is considered in this work because of the numerous benefits to both the consumer and the utility. The PV system typically has a peak generation around mid-day, which generally does not align well with on-site demand with more consumption in the evening. Storage at the PV system is used to store this energy. PV energy, like other renewable energy sources, is subject to rapid weather variations, and the result of this is significant grid instability. In this work, a storage system is optimally charged and discharged to compensate for these fluctuations. This improves the interconnection of PV systems to the grid, and support grid stability. The battery model is presented with general battery dynamics presented by the battery's state of charge (SOC) [78, 79]. The battery energy storage system is characterized by continuous charging and discharging power, therefore $P^h_{b,t}$ and $\bar{P}^h_{b,t}$ are considered continuous variables at time step t.

$$E_t = \sum_{h=1}^{H}(E_0 + \Delta t \sum_{\gamma=1}^{t}(\eta_c P^h_{b,\gamma} - \eta_d \bar{P}^h_{b,\gamma})), 1 \leq t \leq T, \tag{5.9}$$

where E_t is the battery's SOC, E_0 is the initial SOC of the battery, whereas $\eta_c \sum_{\gamma=1}^{t} P^h_{b,\gamma}\Delta t$ and $\eta_d \sum_{\gamma=1}^{t} \bar{P}^h_{b,\gamma}\Delta t$ are the battery energy during the charging and discharge period, respectively.

The following constraints are applied to the battery model:

$$E^{min} \leq E^h_t \leq E^{max}, t = 1, ..., T, \tag{5.10}$$

[5] Eskom Integrated report,2014 <http://http://www.integratedreport.eskom.co.za//>

$$E^{min} = (1 - DOD)E^{max}, \tag{5.11}$$

$$P^h_{b,t} * \bar{P}^h_{b,t} = 0, t = 1, ..., T, \tag{5.12}$$

where (5.10) is the battery energy capacity limits, (5.11) is the relation between E^{min} and E^{max} through the battery's depth of discharge (DOD). (5.12) presents the exclusive operation of the battery because the battery cannot charge and discharge at the same time. This constraints also allows the battery to be in idle mode.

5.3.2.2 Power flows

The total power consumed by a set of all appliances (A) in one household at time step t is given by:

$$\sum_{i=1}^{A} P^h_{i,t} = P^h_{inf,t} + P^h_{flex,t} + P^h_{ngt,t}, \tag{5.13}$$

$$(P^h_{inf,t}, P^h_{flex,t}, P^h_{ngt,t}) \geq 0,$$

while the total power demanded by a household h at each time step is given by,

$$P^h_t = \sum_{i=1}^{A} P^h_{i,t} + P^h_{b,t}. \tag{5.14}$$

The total power demanded by the load in household h at time t, P^h_t, is satisfied by the battery power output $\bar{P}^h_{b,t}$, grid power $(P^h_{m,t})$ and the output $(P_{pv,t})$ charges the battery, hence the power balance equation is given by,

$$\bar{P}^h_{b,t} + P^h_{m,t} = P^h_t, \tag{5.15}$$

where

$$0 \leq P^h_{m,t} \leq P^{max}_m, \tag{5.16}$$

where P^{max}_m is the maximum power capped to the distribution board's maximum power in each household and is computed as; $230V * 60A * 0.75 = 10.35kW$, with nominal single phase voltage and current ratings of $230V$ and $60A$, and an assumed power factor of 0.75.

$$0 \leq P^h_{b,t} \leq P_{pv,t}. \tag{5.17}$$

Constraint (5.17) bounds the battery charge to the PV output. The total power consumption in each household in a day is given by (5.18). k is the controllable appliance index and K is a set of controllable appliances. $P_{k,t}$ is the rated power of controllable appliance k at time t. $u^h_{k,t}$ is the commitment status of appliance k in household h at time t and ρ_t is the TOU electricity price at t.

$$P^h = \sum_{t=1}^{T}(P_{inf,t} + P_{ngt,t} + \sum_{k=1}^{K} P_{k,t}u_{k,t} + \eta_c P_{b,t}). \tag{5.18}$$

The aggregated consumption as seen by the distribution bus from a set of serviced households is given by;

$$P_{bus,t} = \sum_{h=1}^{H}\sum_{t=1}^{T}(P^h_{inf,t} + P^h_{ngt,t} + \sum_{k=1}^{K} P^h_{k,t}u^h_{k,t} + \eta_c P^h_{b,t} - \eta_d \bar{P}^h_{b,t}). \tag{5.19}$$

The individual household energy consumption at time step t is capped to the capacity of the distribution board installed in the house as in (5.20).

$$P^h_{inf,t} + P^h_{ngt,t} + \sum_{k=1}^{K} P^h_{k,t}u^h_{k,t} + \eta_c P^h_{b,t} \leq P^{max}_m. \tag{5.20}$$

5.3.2.3 Appliance operational constraints

Given the predetermined parameters of the controllable appliances; d^h_k, e^h_k and N^h_k, as the beginning and end of the time to which each flexible appliance is to be scheduled, and the duration required to finish the normal operation of each controllable appliance in household h, the following; inequality (5.21) holds.

$$\sum_{t=d_k^h}^{e_k^h} u_{k,t}^h = N_k^h, \forall h, \forall k, \tag{5.21}$$

where

$$N_k^h \leq (e_k^h - d_k^h). \tag{5.22}$$

$$\sum_{t=d_k^h}^{e_k^h} u_{k,t} \cdot u_{k,(t+1)} \cdot u_{k,(t+2)} \cdots u_{k,(t+(N_k-1))} = 1, t = 1, ..., T. \tag{5.23}$$

$$u_{2,t} - u_{6,t} - u_{7,t} = 0 \tag{5.24}$$

$$d_6 + N_6 \leq d_{7+1}. \tag{5.25}$$

$$0 \leq P_{k,t} \leq P_k^{max}, \tag{5.26}$$

where nonlinear constraint (5.23) models the non-interruptible operation of appliances. (5.24) and (5.25) are coordination constraints. (5.24) coordinates lighting with the appliances used in their respective rooms, using the the laundry room as a reference. The time the laundry lights are off is when neither washing machine nor drier is on. (5.25) ensures that, for example, the dryer follows the washing machine. The numerical indices in equality (5.24) and inequality (5.25) correspond to the appliance number index as provided in Table 5.1.(5.26) is the appliance power consumption limit.

$$\sum_{t=1}^{T} (P_{inf,t}^h + P_{ngt,t}^h + \sum_{k=1}^{K} P_{k,t} u_{k,t}^h + \eta_c P_{b,t}^h) \rho_t \Delta t = C^h. \tag{5.27}$$

This constraint models the maximum cost (C^h)that each household is willing to incur within the control horizon. The parameter C is obtained from the consumer's bill and provided in the data section, Table 5.3.

The formulated model is MINLP optimal control problem with control variables $u^h_{k,t}$, $P^h_{b,t}$, $\bar{P}^h_{b,t}$, and $P^h_{m,t}$.

5.4 DATA

Five apartments in a suburb in South Africa, connected to a common point as shown in Figure 5.1 have been used as a case study. Each household is assumed to have a dedicated PV and battery system.

5.4.1 Tariff

The tariff adopted is based on South Africa's TOU Homeflex 1 tariff structure for household consumers. The Homeflex 1 tariff has five charge components[6] as network charge, service charge, environmental levy, off-peak and peak charges. We model these into fixed and variable charges as follows:

$$\rho_t = F_C + V_C,$$

where F_C is a fixed charge and consist of service charge, network charge and environmental levy, while V_C are peak and off-peak energy charges.

$$F_C = R(2.96 + 3.68 + 2.00)/100,$$

and

$$V_C = \begin{cases} R1.7487, & \text{peak time, } t \in \text{[07:00,10:00),[18:00,20:00)} \\ R0.5510, & \text{off-peak time, } t \in \text{[00:00,07:00),[10:00,18:00],[20:00,00:00]}. \end{cases}$$

[6]Eskom tariffs and charges 2011/2012 $< http://eskom.com >$

5.4.2 Appliance data

The maximum rated power of the appliances is specified by the manufacturers and it is indicated on each appliance's electric nameplates. Weekday data for a period of one month on appliance usage in the households under study were collected. Table 5.1 shows common flexible, inflexible and night-time loads with their respective power consumptions. Different power ratings are due to different appliance brands and sizes. It must be noted that depending on the type of consumer, flexibility of appliances differs as shown in Table 5.2 for the duration at which appliances may be committed and this is depicted in Figure 5.3. In Table 5.2, for example; stove usage commitment time ranges varies in all households. Household 1, h_1, proposes to commit stove usage any time from 06:00 to 21:00 making them more flexible on this appliance whereas h_4 is less flexible compared to the former with time ranges of 05:30 to 09:00. One of the practical reasons is that household with non-working family members may be willing to have a less stringent/time scheduling horizon while working class families or families with school-going children, may have to cook within specified times. This observation motivates for further research into actual classification of appliance usage based on family types. Table 5.2 also shows the measured maximum run-time, N_k, of appliance k.

Table 5.1: Appliances types and power consumptions

Index (i)	Appliance	Rated power P_i (kW)				
		h_1	h_2	h_3	h_4	h_5
	Flexible					
1	Kitchen lights			0.11		
2	Laundry room lights			0.11		
3	Microwave	0.8	1.5	0.6	1.2	0.6
4	Stove	2.2	2.0	2.4	2.0	2.0
5	EWH	2.0	2.0	2.0	2.0	2.0
6	Washing machine	2.0	2.4	2.2	2.0	2.0
7	Clothes dryer/spin	2.0	0.6	2.0	0.6	0.6
8	Vacuum cleaner	0.8	0.8	0.4	0.8	0.35
9	DVD player	0.025	0.025	0.025	0.015	0.015
	Inflexible					
10	TV room lights			0.11		
11	Refrigerator	0.35	0.4	0.25	0.35	0.15
12	Television	0.133	0.1	0.25	0.1	0.09
13	Decoder			0.07		
	Night loads					
14	Breadmaker	1.5	1.5	1.6	1.2	-
15	Dishwasher	1.5 1.2	1.2	1.5	1.5	-

Table 5.2: Appliance baseline data for flexible appliances

Appliance	Duration (d_k, e_k),					Run-time N_k (min)				
	h_1	h_2	h_3	h_4	h_5	h_1	h_2	h_3	h_4	h_5
Kitchen lights	As kitchen appliances									
Laundry room lights	As laundry appliances									
Microwave	06:00-21:00	04:00-18:00	08:00-11:00	05:30-09:00	01:00-19:00	6	8	6	6	9
Stove	06:30-15:00	06:00-15:00	08:00-11:00	05:30-09:00	01:00-15:00	54	45	48	62	36
EWH	06:00-15:00	09:15:00	23:00-04:00	16:00-23:00	-	180	120	180	180	180
Washing machine	10:00-15:00	18:00-22:00	15:00-17:00	16:00-22:00	01:00-19:00	60	60	60	60	60
Clothes dryer	10:00-15:00	18:00-22:00	15:00-17:00	16:00-22:0	01:00-19:00	30	30	30	30	15
Vacuum cleaner	10:00-18:00	09:00-12:00	08:00-15:00	08:00-14:00	01:00-19:00	12	24	16	18	10
DVD player	10:00:23:00	08:00-23:00	08:00-23:00	08:00-22:00	01:00-19:00	120	180	120	120	120

Individual households shows that most of them portray different consumptions; h_1 displays different consumption behaviour with one evening peak. However, household h_5 is the lowest consumer with missing data for EWH which was non functioning at a time of data collection.

Based on the data obtained, we determined the percentage of flexible load in each household as $\frac{\sum_t^T P_{flex,t}}{\sum_t^T \sum_{i=1}^A P_{i,t}^h} * 100$, and it is found that it ranges from 20-42%. Figure 5.4 shows the baseline load profile for aggregated total load of the five households and the load for inflexible and night loads. It is observed that the baseline has three peaks, morning, lunch and evening peak, with morning as the highest peak at 09:00-10:00. This shows that the highest consumers are stay-home families, as revealed in Figure 5.4 with h_2, h_1 and h_3 as morning peak high contributors.

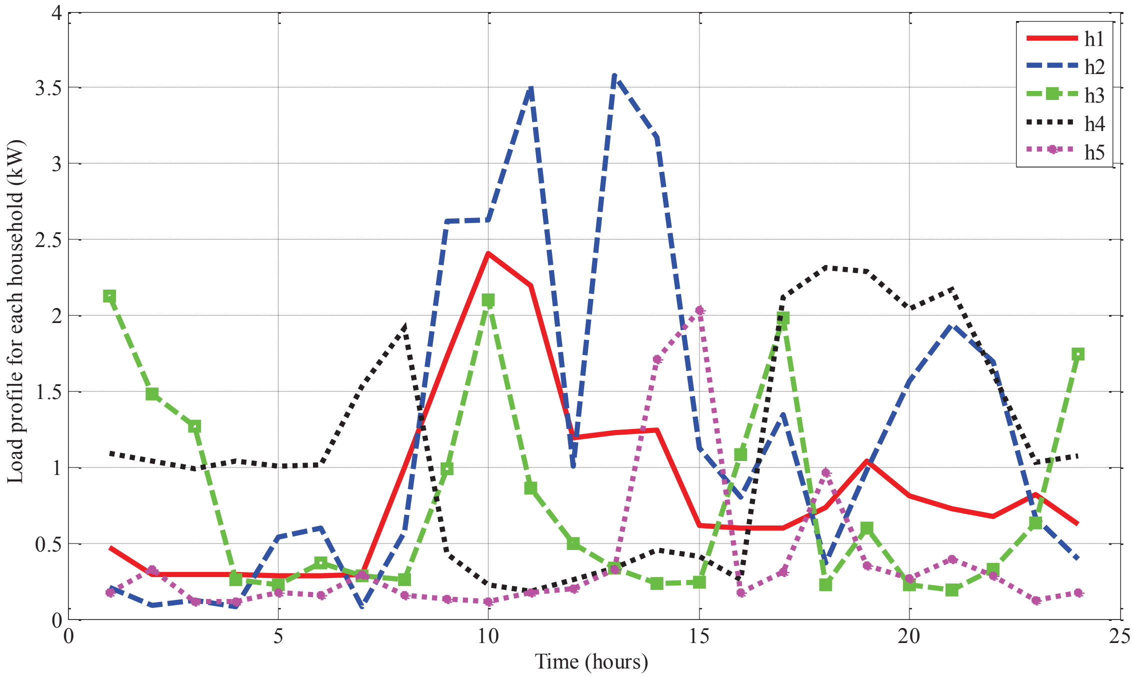

Figure 5.3: Baseline demand for each household

Table 3 provides data for the maximum budget that each household is willing to incur in the study horizon. This data is obtained from the bill of each household.

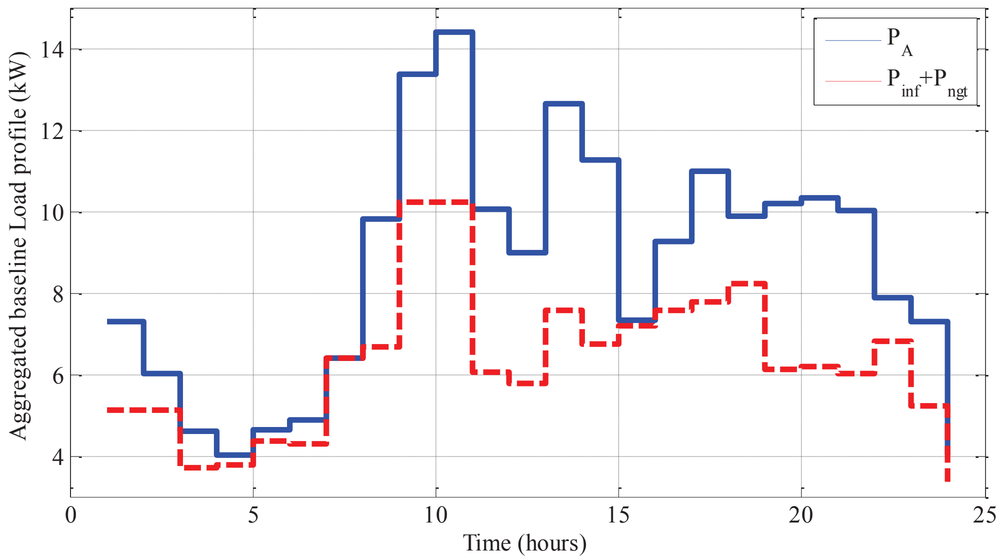

Figure 5.4: Aggregated baseline demand for five households

Table 5.3: Maximum budget C

Household	h_1	h_2	h_3	h_4	h_5
Maximum daily bill(C) (R)	15.90	23.08	12.16	22.57	10.23

5.4.3 P_{pv} and battery data

Each household is assumed to have the same battery and PV. The battery bank data is provided in Table 5.2 and the data for PV is shown in Figure 5.5; this data is adopted from [75]. The battery capacity is an assumed value of 10 kWh. The minimum discharge capacity of 50% has been shown to sustain the lifespan of the battery [76].

Table 5.4: Battery data

Battery capacity	10kWh
η_c	75%
η_d	100%
DOD	50%

5.5 SOLUTION METHODOLOGY

The MINLP optimization problem (5.1)-(5.27) is solved with an optimization solver, SCIP, available in the Matlab interface OPTI toolbox. The simulation study is performed for 24 hours at a sampling time of 15 minutes. SCIP is currently one of the fastest non-commercial solvers for MIP and MINLP. It is also a framework for constraint integer programming and branch-cut-and-price[20,21]. It uses Interior Point Optimizer (IPOPT) and SoPlex as non-linear and integer algorithms. SoPlex is an advanced implementation of the revised simplex algorithm for solving linear programs. It features preprocessing, exploits sparsity, and provides primal and dual solving routines. It is the default LP solver in SCIP. IPOPT is an open-source solver for large-scale nonlinear programming. IPOPT implements a primal-dual interior point method and uses line searches based on filter methods[7,22]. The solver offers solutions to problems of the form:

$$\min f(x), s.t., \begin{cases} Ax \leq b, A_{eq}x = b_{eq}(\text{linear constraints}) \\ c(x) \leq d, c_{eq}(x) = d_{eq}(\text{nonlinear constraints}) \\ Lb \leq x \leq Ub(\text{variable bounds}) \\ x_i \in \mathbb{Z}(\text{integer decision variables}) \\ x_j \in \{0,1\}, i \neq j(\text{binary decision variables}) \end{cases}$$

The measured results are compared with simulation results to demonstrate the effectiveness of the algorithm.

5.6 SIMULATION RESULTS AND DISCUSSION

This section presents simulation results of two cases. Case 1 demonstrates an energy management system that combines DSM strategies with a dedicated PV and storage system under TOU tariff. Case 2 presents the results of an investigation on the joint influence of dynamic electricity price and CO_2 emissions in a DR program.

5.6.1 Case 1

To make this case concise, we start looking at one household then aggregated households with an objective; $\min J = w_1 J_e + w_2 J_I$ where $w_1 + w_2 = 1$. Simulation results are given at assumed $w_1 = 0.2$ and $w_2 = 0.8$.

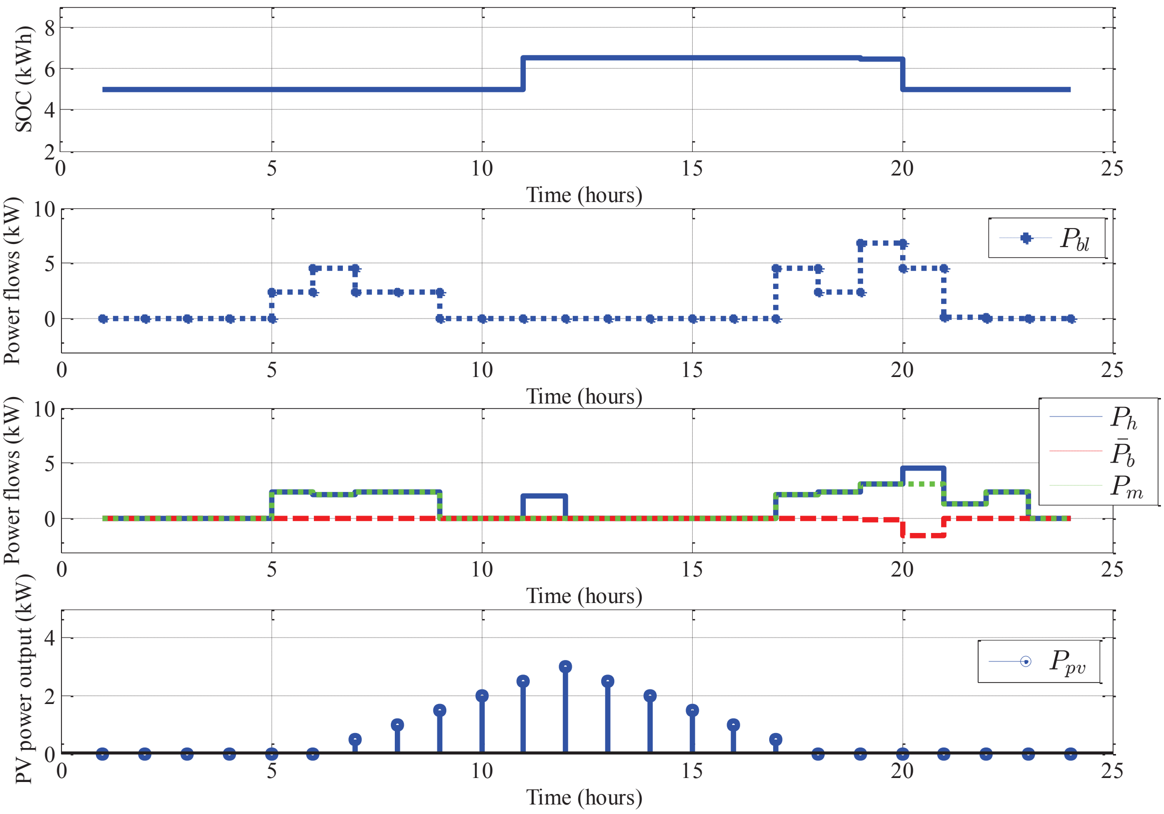

Figure 5.5: Simulation of h_3

The results in Figure 5.5 show one household's results with the battery's SOC, power flows and P_{pv}. The battery charges at hour 11; at that time it is charged by the PV power. The baseline cost of flexible appliances excluding the battery is R28.96. Optimal cost due to appliances load shifting is R23.08, a cost saving of 20.08%. This cost could have been R24.20 without the PV because of charging of the battery. The overall cost due to load shifting, battery and PV is R20.83, a cost saving of 28.05%. This shows that the PV and battery contribute 7.97%. Note that the contribution share is sensitive to the weighting factors as demonstrated in case 2, therefore the consumers' preferences affect the savings. The inconvenience cost at these weighting factors however is R11.41, which one can argue that it is a relatively large value that may not be economical to the electricity suppliers. The power is reduced from 6.794 kW at hour 19 to 4.58 kW owing to appliance shifting and battery discharge.

Figure 5.6; shows the results of the aggregated households assumed to have the same weighting factors of $w_1 = 0.2$ and $w_2 = 0.8$. The baseline power as seen by the distribution bus and the optimal power seen by the same bus after optimal control: shows a total power reduction seen by the distribution bus from 205.50 kW to 176.44 kW, a reduction of 14%. A total energy cost reduction from R164.18 to R139.21 of 15.21% is realized by aggregated households. The DR combined with PV and battery show that the aggregated strategy can reduce the power demanded from a distribution system by a significant amount and thus relieve the power system network and according some residential members significant collective savings. It must be noted in Figure 5.6 that the maximum peak present in the morning still occurs because the remaining part of the peak occurs after the peak times later than 10am and since the prices at that time are relatively lower, the peak remains. This also applies to the mid-day peak. This is also due to unavailability of PV power where the battery starts charging at around 11:00. However, in the evening peak a significant reduction is realized, since the TOU tariff is high during those times and the battery is fully charged. This also shows the effectiveness of the optimizer scheduling both appliances and the battery.

5.6.2 Case 2

In this case we consider carbon emissions with the objective $\min J = w_1 J_e + w_2 J_I + w_3 J_c$ where $w_1 + w_2 + w_2 = 1$. We investigate the joint influence of dynamic electricity price and CO_2 emissions. As in case 1, we look at one typical household with typical controllable loads. Figure 5.7 shows the results of the same household in case 1 with $w_1 = w_2 = w_3 = 0$, where the consumer does not place value on any of the sub-functions.

Simulation results in Figure 5.8 are given at $w_1 = 0$, $w_2 = 0$ and $w_3 = 1$, that is, the case of an environmentally sensitive consumer places high importance on the carbon emissions. Both figures show that for different preferences, the consumption profile is different, hence the costs also vary accordingly.

The effect of different combinations of the weighting factors on costs, considering extreme

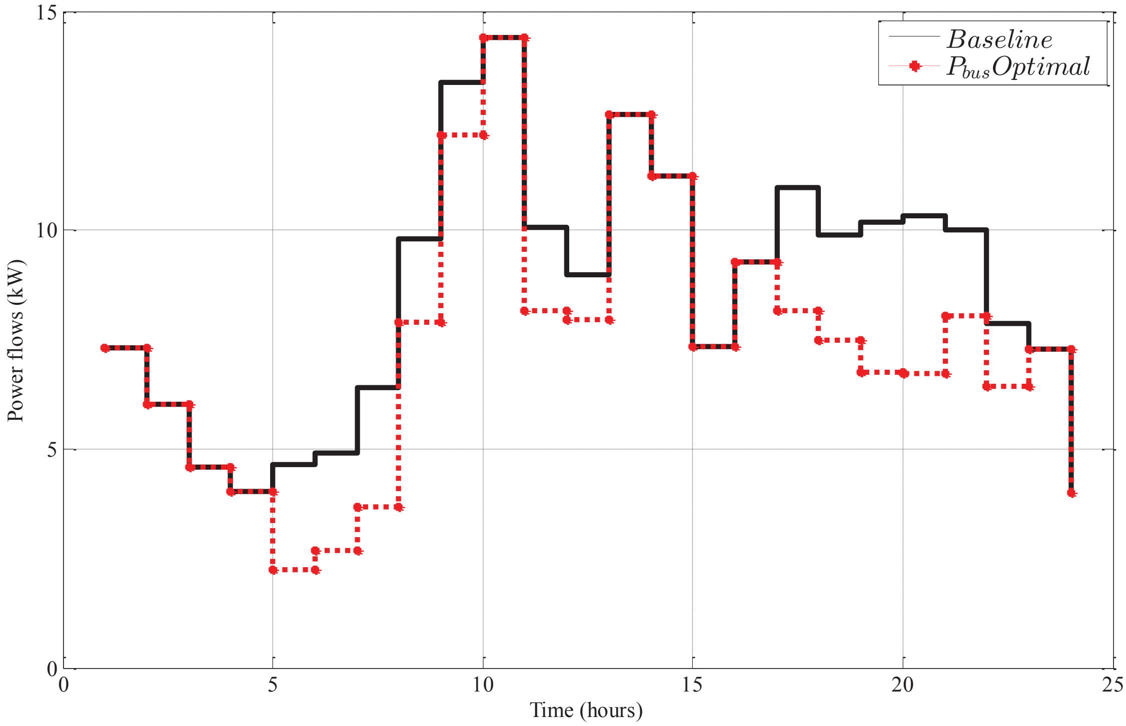

Figure 5.6: Simulation of aggregated households

cases, is summarized in Table 5.5. It is demonstrated that the consumer's preferences on the cost sub-functions of energy, inconvenience and carbon emissions affects the consumption pattern. A different weighting factor shows the consumer's different preferences regarding the different costs. It is to be noted that the selection of the proper value of w is subjective, as it is dependent on the user's preference. The consumer could be guided by their level of awareness and understanding on the sub-function costs. These results are important for both the consumer and the electricity suppliers, as they illustrate the optimal decisions that needs to be made in the presence of multiple objectives. This could offer flexibility to the consumer.

In Table 5.5, five cases of preferences are presented, of which four are extreme and for comparison, an additional non-extreme scenario is included. In the first scenario, the consumer does not place any priority on any of the cost functions. In the second scenario, the consumer's priority is the energy cost and he does not care about the other two. The results concur with practical expectation in that; where the consumer places more value, the respective cost will be minimal. High value on energy cost, case 2, gives the lowest cost of R18.60, while high

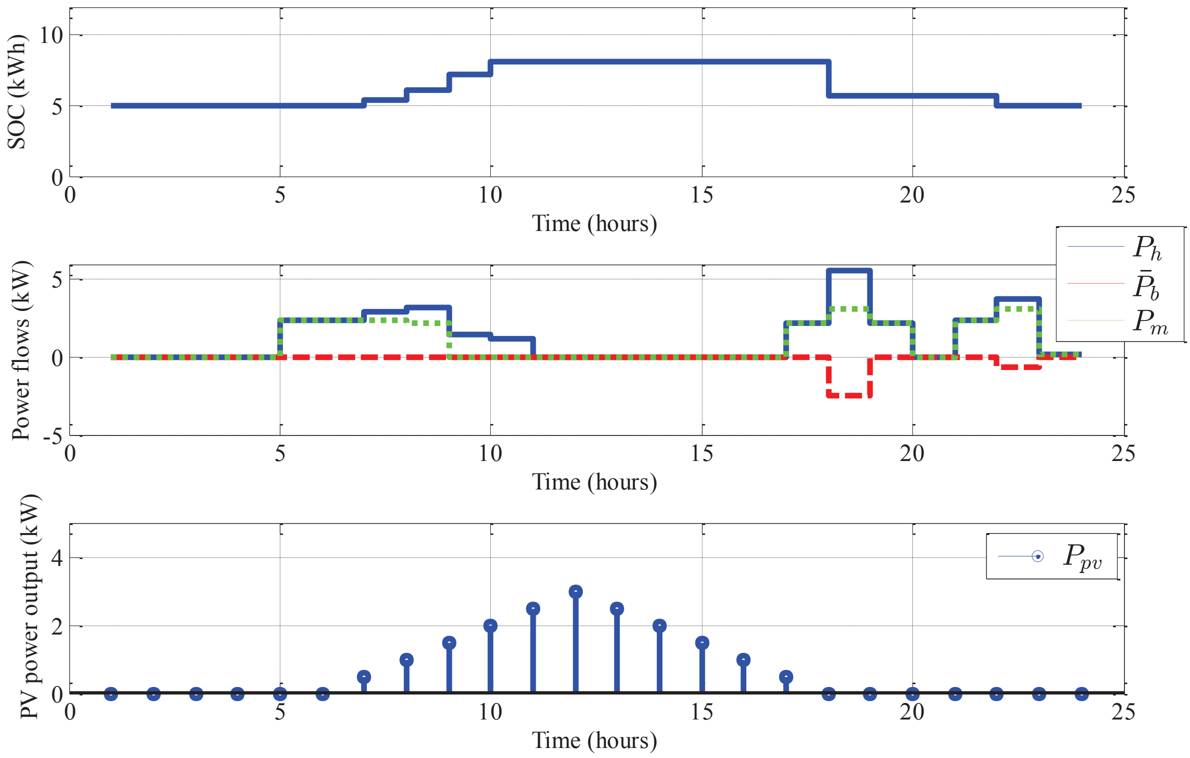

Figure 5.7: Simulation results for h_3 with $w_1 = w_2 = w_3 = 0$

value on inconvenience, case 3, gives the lowest inconvenience cost of R4.89 and high value on carbon emissions cost gives the lowest value of R3.40. Case 5 is a typical non-extreme preference with in-between values, where the cost of the battery is given by the cost of charging the battery against the savings achieved form battery discharge. It is shown that the other preferences may involve less cost of using the battery.

The simulation results for the aggregated households h_1 to h_H show carbon emissions saving under the weighting factors that are assumed to be same for all households. The baseline aggregated carbon emissions is 203.44 kg while the optimal solution gives a reduced carbon emission of 174.67 kg, 14.14% savings. Carbon costs are respectively R26.91 and R23.11. This shows that carbon emissions could give customers an environmental motivation to shift or reduce loads during peak hours, as it would enable co-optimization of electricity consumption, inconvenience and carbon emissions costs reductions. This could also be used to motivate consumers to opt for more usage of renewable resources

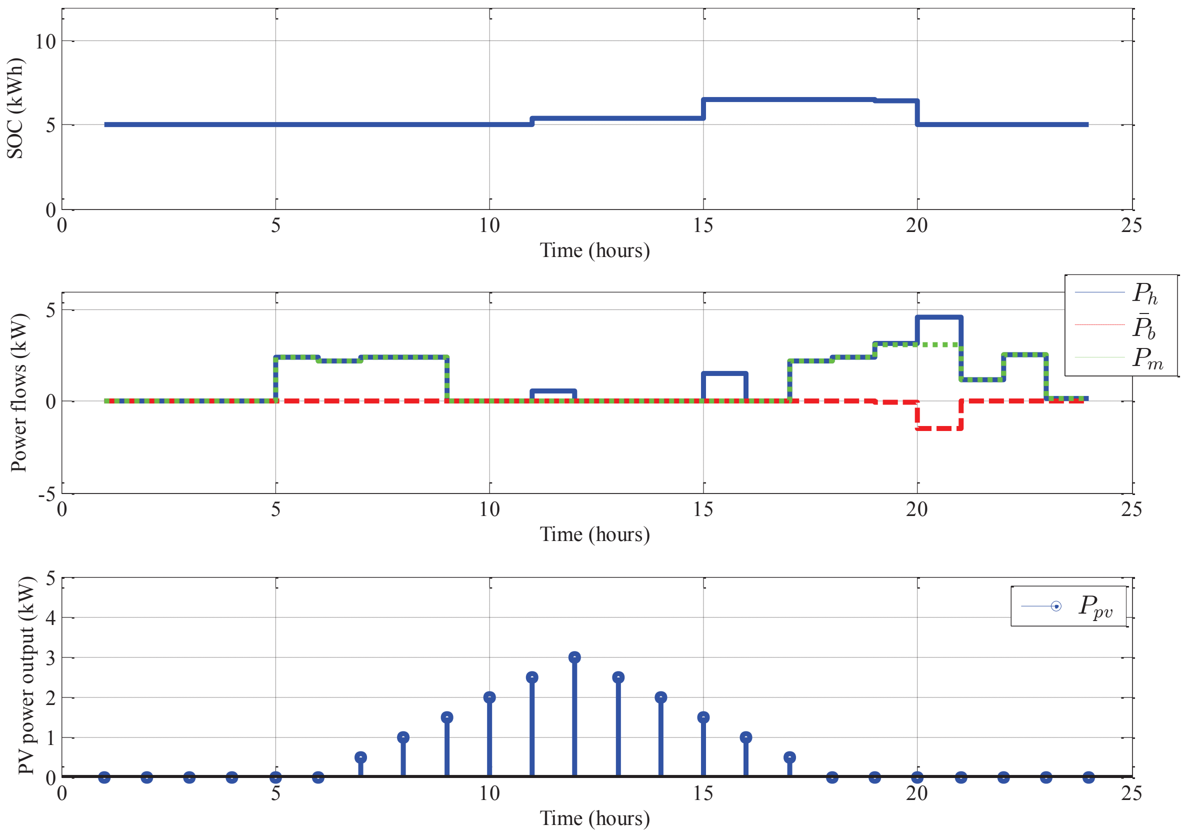

Figure 5.8: Simulation results for h_3 with $w_1 = w_2 = 0$ and $w_3 = 1$

5.7 ECONOMIC ANALYSIS

Since the problem modelled in this work entails combined DSM strategies, it is assumed that the consumer does not bear the cost of demand response which is usually covered by the utility, therefore, this economic analysis is performed on the usage of PV and battery system on such a combined DSM strategy.

There are different methods used to perform economic analysis of systems in the literature. These methods include but not limited to net present value (NPV), pay back period (PB) and discounted present value (DPV) [18, 22, 100, 102, 104, 110]. In this chapter we adopt the DPV method expressed in[10] [110] to determine the time needed to recover an investment on the usage of PV and battery system based on the discounted cash flows of the investment.

[10] Discounted present value calculator, < *http://www.aqua-calc.com/page/discounted-present-value-calculator* >

Table 5.5: Effect of weighing factors on costs for a typical household

No.	w_1	w_2	w_3	J_e (R)	J_I (R)	J_c (R)
1	0	0	0	21.76	10.31	3.53
2	1	0	0	18.60	9.45	3.52
3	0	1	0	27.92	4.89	3.88
4	0	0	1	27.89	10.42	3.40
5	0.2	0.4	0.4	21.44	5.21	3.46

The discounted payback period accounts for the time when the invested capital has been recovered or has reached a break even point.

$$DPV = \frac{FV}{(1+r)^n}, \tag{5.28}$$

where FV represent future value of money in reference to today's value, which is achieved by discounting its present value, whereas n is the number of years, and r is the discount or interest rate given as 5.75% for the current month, July 2015 as South African inflation rate[11]. In order to make an economic analysis of the PV-battery system, certain assumptions are made.

The PV and battery costs entails capital cost, operational and maintenance (O&M) costs as shown in Table 5.4. Since our study horizon is one day we annualize our costs.

In [103–105, 111], the O&M cost of a PV-battery has been estimated to a specific annual value or some online sources estimate the annual O&M cost to be around 2-2.5% of capital cost and in this work we use less conservative value of 2.5%. Calculation of savings brought by the optimal use of the PV-battery system is performed as follows.

The energy from the PV-battery system utilised by the consumer is given by annual energy output to consumer (AEO) as in (28);

[11] Current market rates, South African reserve bank, July 2015, $< http : //www.resbank.co.za/Research/Rates/Pages/CurrentMarketRates.aspx. >$

Table 5.6: Approximate cost of components

Component	Approximate cost (R)
Solar modules	59 550.00
Deep cycle battery	11 559.00
Inverter and accessories	7,172
Energy controllers	9,557
Installation cost	5,430
Sub total	*93 268*
Operation and maintenance cost (@2.5% fixed annual)	2 331.70
TOTAL	95 600.00

$$AEO = \sum_{t}^{T} \bar{P}_{b,t} \Delta t \cdot 365. \tag{5.29}$$

Then equality (29) is used to determine the percentage energy saving that is brought by the use of PV-battery system;

$$\%S = \frac{AEO}{AEC}, \tag{5.30}$$

the percentage of the consumers electric bill that is covered by the PV-battery system is $\%S$; obtained from the system's annualised energy output, AEO and annualised energy consumption AEC from the monthly electric bill from municipality which coincides with the measured values determined from Figure 5.4. The annualised cost savings (AES) due to PV-battery system is determined from the product of the annual bill charge and $\%S$.

$$AES = \%S \cdot AEC \cdot \xi. \tag{5.31}$$

Note that the monthly bill charge of $R1.36kWh$ for South Africa is used as a flat electricity price prior to DR, otherwise $\xi = \rho_t$. The energy cost saving for a typical household, say h_4 is shown in Table 5.7.

Table 5.7: Energy cost saving due to PV-battery system for h_3

AEO (kWh/yr)	AEC (kWh/yr)	$\%S$	AES (R)
2086	7080	0.2946	28 582

The results in Table 5.7 show that the use of PV-battery system yields an annual energy cost saving of R3089.90 to the consumer. This is within reasonable values of 20-45% reported in most literature. Then this value of AES is used as the optimal benefit of using PV-battery system in calculating the discounted present value. Table 5.7 shows the revenue for h_4 from solar energy sales and the household's benefit on cost savings emanating from the proposed optimal control strategy.

Table 5.8: Payback Period

Years	0	1	2	3	4	5	6
Capital cost	(93 268.00)						
O&M (@2.5% Capital cost)		(2331.70)	(2331.70)	(2331.70)	(2331.70)	(2331.70)	(2331.70)
Optimal benefit		28 582	28 582	3 28 582	28 582	28 582	28 582
	(93 268.00)	26 250.3	26 250.3	26 250.3	26 250.3	26 250.3	26 250.3
Discount factor @5.75%	1	0.95	0.89	0.85	0.80	0.576	0.72
Discounted cash flows	(93 268.00)	24 822.98	23 473.27	22 196.94	20 990.02	19 848.71	18 769.47
Discounted PBP	Years	D-cashflows	C-cashflows				
	0	(93 268.00)	(93 268.00)				
	1	24 822.98	(68 445.02)				
	2	23 473.27	(44 971.76)				
	3	22 196.94	(22 774.81)				
	4	20 990.02	(1 784.80)				
	5	19 848.71	18 063.92				
	6	18 769.47	36 833.39				
Payback period	**4.09 years**						

As can be seen in Table 5.8, the assumptions made are that the operation and maintenance costs and optimal benefits are constant throughout the projected years into the future. This assumption implies that exclusion of weighted sum of capital cost the pay back period is reduced. It can be seen from the table that in this case, the payback period of h_4 is 4.09 years. It is however acknowledged that this is an estimate based on the assumptions made. A more precise results could be obtained from the actual sizing of the PV-battery system and consideration of the wacc which cannot be reliably estimated at this point.

5.8 CHAPTER SUMMARY AND CONCLUSION

Optimal control strategy through optimal scheduling of resources during a demand response program has been studied in this chapter. In this study, the first part, proposes an energy management system that combines DSM strategies with a view to minimize the consumer's cost and reduce the power consumed from the grid, thereby promoting power system stability. A combination of appliance scheduling, dedicated PV and a storage system under TOU tariff shows that power drawn from the distribution bus reduces by 14% while cost savings are 15.21%. This strategy of DR combined with PV and battery shows that the aggregated strategy can reduce the power demanded from a distribution system by a significant amount and thus relieve the power system network and afford some residential members significant collective savings. The second part of this study shows that consumption habits may require other incentives to change in addition to the proposed energy and inconvenience cost. Knowledge of carbon emissions can incentivize investment in renewable energy at household level. It is also demonstrated that the consumer's preferences on the cost sub-functions of energy, inconvenience and carbon emissions affects the consumption pattern. These results are important for both the consumer and the electricity suppliers, as they illustrate the optimal decisions that needs to be made in the presence multiple objectives. In the measured data, however, it was discovered that the level of flexibility on the 'assumed' controllable appliances may vary between households. Economic analysis on consideration of a PV and battery system has also been studied where it has been shown that the payback period 4.09 has been estimated based on the data provided and the assumptions made.

CHAPTER 6

SUMMARY, CONCLUSIONS AND FUTURE WORK

6.1 SUMMARY

The objective of this research is to develop optimal control models to study residential load control under demand response, TOU program. The study looked at the formulation of a MINLP optimal control models for optimal scheduling of household resources. Simulation results revealed that there is potential for the consumers to gain economic benefits and smoothed power consumption for the utlity's benefit. However, a number of factors discovered in this research, as stated below, affects the level of savings. It is also shown that consumer cost, valley filling and peak clipping could be enhanced further by considering other resources.

Chapter Two provides an extensive literature review on demand response and residential demand response.

Chapter Three provides initial formulation of a mixed integer nonlinear optimization mathematical model to study appliance scheduling under DR with consideration of the incentive offered during peak times in addition to the time differentiated electricity prices, and also the inconvenience. The results show that; through optimal scheduling of appliances during a time varying electricity tariff, the consumer can reduce their energy consumption during peak times through load shifting and curtail consumption due to incentive. The model also minimizes the inconvenience that is brought by the proposed optimal appliance switching status against the baseline. A sensitivity analysis of the inconvenience cost coefficient show that the total cost savings is affected by the inconvenience coefficient cost. The importance of this analysis is that the consumer is able to choose according to their preferences with regard to the cost and the inconvenience. This study benefits the consumer economically and the utility in terms of stabilising the power system network through peak reduction and valley filling. Consideration of the inconvenience enables the consumer could affect the level of participation of the consumer in the DR program.

Chapter Four of this research formulated the model and studied appliance scheduling in the presence of a storage system and consideration of appliance coordination. In addition to the preceding results, consideration of appliance coordination brings variation in the results obtained. A further energy cost reduction is achieved by using a battery, which promotes further peak shaving as it discharges during peak times. However, since the battery charges during off-peak times, it provides valley filling. This not only affects an energy cost saving for the household, but also promotes energy balance in the power system, which the utility pursues as a global need. The battery does not bring about a significant improvement when compared with load shifting, which yields a significant energy cost saving because of the charging component of the battery, which has a power consumption cost. Consideration of appliance coordination reduces the cost by a very small amount. It has been found that the solution obtained is sensitive to the amount the consumer is willing to pay or the budget. This, however, shows that the consumer can also use their budget to regulate the algorithm's outcome.

An optimal control model with a dedicated PV and storage system is formulated in Chapter 5. This part of the study considered multiple households and the first part, proposes an energy management system that combines DSM strategies with a view to minimize the consumer's cost and reduce the power consumed from the grid, thereby promoting power system stability. A combination of appliance scheduling, dedicated PV and a storage system under TOU tariff shows that power drawn from the distribution bus as well as the cost savings are reduced. This strategy of DR combined with PV and battery shows that the aggregated strategy can reduce the power demanded from a distribution system by a significant amount and thus relieve the power system network and afford some residential members significant collective savings. The second part of this study shows that consumption habits may require other incentives to change in addition to the proposed energy and inconvenience cost. Knowledge on carbon emissions can incentivize investment in renewable energy at household level.

It is also demonstrated that the consumer's preferences on the cost sub-functions of energy, inconvenience and carbon emissions affects the consumption pattern. These results are important for both the consumer and the electricity suppliers, as they illustrate the optimal decisions made when there is multiple objectives.

6.2 CONCLUSIONS

The objectives of this study have been accomplished albeit with room for further study as in the following subsection. The optimal control problem formulations verified through simulations revealed the following conclusions from this research;

- In the presence of variable electricity prices, the consumer can shift their shiftable appliances to less expensive off-peak prices. This can accord the consumer some economical savings and the utility some balanced power drawn from the system.

- In addition to variable electricity prices, the incentive offered during peak times can motivate the consumer to curtail their loads during peak times hence promoting more savings and peak reduction.

- It has been found out that inconvenience cost affects the energy and cost savings because the level of savings depends on the degree at which the consumer may be willing to be inconvenienced by the proposed optimal schedule.

- Consideration of appliance coordination is vital to the appliance scheduling problem in that it affects the solution as some appliances are scheduled relative to another, for example the clothes drying follows the washing and the television is operated either with the decoder or DVD player but not both appliances concurrently with the television set.

- The other conclusion that emanates from this research is that the energy cost savings are affected by the consumer's budget or how much they are willing to pay. This could be used by the consumer to regulate their consumption. However, if the consumer is not budget constrained, this could work against the goal of DR of according consumers cost savings while at the same time benefiting the utility with peak reductions or smoothing of the power system consumption.

- In this research, it is also found out that the use of the storage system could accord the consumer some daily savings when the storage system is scheduled optimally. This also promotes valley filling and peak shaving which is of utmost importance for the power system stability. However, the battery alone offers marginal savings due the consumption during charging.

- When the battery is used with a PV system as dedicated systems, more energy savings are realised and more reduction in the power consumption from the grid is achieved. The economic analysis also shows that the consumer could recover their investment on a dedicated PV and battery within 5 year period. It is also shown in this study that the consumer could use not only the energy cost, inconvenience and budget to regulate their consumption but also the knowledge on environmental impact. Therefore, the developed model to investigate the joint influence of price and CO_2 emissions revealed that CO_2 emissions could give customers an environmental motivation to shift loads during peak hours.

6.3 FUTURE WORK

This topic is an active area of research and there is room for further improvement to achieve an implementable models, however the list may not be exhaustive;

- The electricity consumption in a household primarily depends on the power consumption of the electrical appliances and the behaviour of the occupants using them. Modelling of consumer behaviour has remained one of the greatest challenges in this area because assumptions are made that there is some similarity between consumers. It is discovered from field measurements in this work that flexibility of appliances differs depending on the type of consumer. One of the practical reasons is that household with non-working family members may be willing to have a less stringent/time scheduling horizon while working class families or families with school-going children, may have to commit their appliances within specified times. This observation motivates for further research into actual classification of appliance usage based on family types.

- There is a need to develop a scientific method to estimate or predict a pareto-optimal value of inconvenience cost coefficient because it has been assumed that the coefficient is equivalent to the TOU tariff which may not be profitable to the electricity suppliers.

- In the development of a model to investigate the joint influence of price and CO_2 emissions, it emerged that CO_2 emissions could give customers an environmental motivation to shift loads during peak hours, as it would enable co-optimization of electricity consumption costs and carbon emissions reductions. Impact on environmental education on DR needs further investigation.

- Impact of external weather on the cost savings also needs to be investigated in the models because the location where DR savings are anticipated may also be affected by external weather.

- In this work, a model for integrating DR and EE is introduced, however, more consideration of these models to incorporate other types of both DSM strategies is still a major research gap in this area because this type of integration has yet to reach the mainstream; as organization, technical and policy barriers are hurdles in DSM programs as already outlined in Chapter one.

- The optimal control formulations in this work are deterministic; however, world problems almost may invariably include some unknown parameters. This motivates the use of stochastic and robust optimization models which utilize models of uncertain parameters in order to make the best decisions and consideration of performance metrics to evaluate the performance of the stochastic model.

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APPENDIX A

ENERGY AUDIT DOCUMENTS

Due to the complexity of the research problem, it is provided in this section the documents that were developed by the lead researcher. It was found necessary to solicit for the consent of the participants in carrying out this exercise because of the involvement of human beings. The initial stage involved qualitative data collection by means of an in-depth interview as per the attached documents. After consent was granted, quantitative data collection in participating households was performed.

Initially the quantitative data monitoring was applied systematically to an individual household and then to the multiple households.

A.1 CALL FOR PARTICIPATION DOCUMENTS

A.1.1 Letter of participation

Department of Electrical Electronic and Computer Engineering
Hatfield, 0002, Pretoria
E-mail: setlhaolo@tuks.co.za, dsetlhaolo@gmail.com

Dear Sir/Madam

Warmest greetings!

REQUEST FOR PERMISSION TO DO ENERGY MESUREMENT IN YOUR HOUSEHOLD

My name is Ms. D. Setlhaolo and I am conducting research for my Doctoral thesis involving measurement of energy consumption and behaviour patterns in households. This research is conducted under the supervision of Prof. X. Xia in the department of Electrical Electronic and Computer Engineering in University of Pretoria.

I kindly solicit your help to realize our research objectives. In view of this, we would like to request your participation by answering our questionnaire and allowing us to measure your energy consumption for a period of at least ONE month. It is guaranteed that all information derived herein will be treated with utmost confidentiality. The benefits of participating in this exercise are free energy audit of your house and free recommendations that may help you save energy and money. There are no risks involved in this study.

To ensure that this process delivers its intended results, further information is provided in the attached information documents; participant information sheet, consent forms and explanation of the audit exercise and energy monitors are provided. A discussion meeting could also be arranged with you after signing of consent forms.

Your agreement to participate is highly appreciated.

Thank you for your kindness.

Regards,

Ditiro Setlhaolo

0845432770,setlhaolo@tuks.co.za, dsetlhaolo@gmail.com

Audit No.______________

A.1.2 Energy audit process

Department of Electrical Electronic and Co
Engineering
Hatfield, 0002, Pretoria
E-mail: setlhaolo@tuks.co.za, dsetlhaolo@gmail.com

Lead researcher: Ditiro Setlhaolo
Contact number: 084 543 2770

Participant information sheet

You are invited to participate in research with the title: *Household energy use and management*

I am a doctoral student at the University of Pretoria and will be conducting energy audits about energy efficiency in Pretoria. The process to be followed is explained below:

1) Monitoring electricity use in your home for the period of four weeks – the energy audit
Time required: Two 1-hour slots (for the installation and the removal of monitoring equipment) and 30 minutes per week for evaluation.
Duration of monitoring: 4 weeks
Risks or benefits: No risks are envisaged. The benefits include personalised free feedback information about your household's energy use and free advice on how to save energy and money.
Schedule of participation: Appointments will be made with you at a time that suits you.
Purpose of the monitoring: The installation of the monitoring equipment's will be done by a trained energy advisor, who will come into your house and in collaboration with you, install energy monitoring devices. These devices will measure the amount of electricity used in your household and energy use of sampled appliances. One is installed at the distribution box in your home, but does not require cutting of any wires. Usage data is sent via a transmitter and collected by a receiver. This information can then be downloaded on a computer when the advisor or the researcher comes to remove the system. Others are plugged in sockets before the appliances.

The devices should not be a hindrance to you or anybody else in your household. You will be requested to keep the monitoring equipment's safe and avoid changing anything in the set-up for the duration of the FOUR weeks. You will also be requested to provide the researcher with a recent copy of your electricity bill to compare your historical electricity usage to your current electricity use by means of municipal data. This, however, is not compulsory.

Confidentiality and access to gathered data: To ensure that only the researcher has access to your personal information, you will be allocated an audit number. This will be used as your identifier throughout, and no personal information will accompany data usage. Only the lead researcher and the University's academic staff will have access to the data usage (not personal information, just the audit number).

2) Feedback
Each household will receive written feedback about their household energy use within four weeks of the electricity monitor being removed from their homes. More general feedback about the findings of the study as a whole will be published in the form of an article and may only be available after the completion of my doctoral studies, i.e. at the end of 2015.

Thank you for volunteering to participate!

Please note:
The University of Pretoria will not be held liable for any damages or injuries incurred during participation in this project.

Your rights: There are no risks involved in this study. Please take note that you are under no obligation to continue your involvement in the project. Should you wish to withdraw, it will be without negative consequences and all gathered information will be destroyed.

The lead researcher can be contacted at the following number:

Ditiro Setlhaolo
Cell phone: 084 543 2770
E-mail: dsetlhaolo@gmail.com

If you have any questions, suggestions or requests, please contact me.

____

Ditiro Setlhaolo
Lead Researcher

Audit No. ________________

A.2 ENERGY MONITORS

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

100
1908 - 2008
UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Department of Electrical Electronic and Computer Engineering
Hatfield, 0002, Pretoria
E-mail: setlhaolo@tuks.co.za, dsetlhaolo@gmail.com

Explaining the energy Efergy E2 and Efergy socket monitors and how they work.

1. Efergy E2 monitor

The Efergy E2 is a wireless electricity monitor also allows you to electrical energy use in download your house. This makes it very easy to track your energy usage and the impact of the changes you make on your consumption and electricity bill.

Components and their functions;

- *CT sensor unit*: This unit is clipped onto your electricity metre's feed cable.
- *Transmitter unit* : This unit links to the sensor cable and sends information to the display unit
- *Display unit*: This unit displays the information on energy usage. It displays energy used (the recording is taken approximately every 10 minutes) and the cost of the energy in monetary units being consumed. The E2 also provides CO2 emissions, calculating the carbon footprint generated by your electricity usage

The device is not intrusive and does not require rewiring; no wires or cables need to be cut, removed or modified to perform this installation.

The memory function stores your energy data so you can view it by day, week or month or as an average. You can even view hourly data over the previous 8 months.

All of this easily accessible information will help you to determine how best to reduce your energy use so you can start saving energy and money straight away.

2. Energy monitoring socket

The energy monitoring socket allows you to monitor individual electrical appliance by measuring not only the energy consumption but also how much they cost, hence you become aware of potential savings.

The unit is simply installed by plugging into the wall socket and the appliance into the unit. The programming of the device will be performed by the energy auditor.

Please note that it is important for the devices not to be tampered with during this study.

Contact details
Lead researcher: Ditiro Setlhaolo
Contact number: 084 543 2770 email: setlhaolo@tuks.co.za, dsetlhaolo@gmail.com

A.3 CONSENT FORM

A.3.1 Energy audit

Department of Electrical Electronic and Computer Engineering
Hatfield, 0002, Pretoria
E-mail: setlhaolo@tuks.co.za, dsetlhaolo@gmail.com

Lead researcher: Ditiro Setlhaolo

Contact number: 084 543 2770, e-mail: dsetlhaolo@gmail.com

Consent form – Energy audit

Please note: The University of Pretoria will not be held liable for any damages or injuries incurred during participation in this research.

Please read the participant information sheet carefully before committing to participate in this study.

I understand that there are no risks involved in this study and that I am free to withdraw from this study at any stage of the research.

By signing this form I acknowledge and agree to the following:

- I agree to participate in a four-week home energy audit and all that it entails;
- I agree to provide the researcher with a recent copy of my electricity bill;
- I agree to ensure that the equipment remains in my house for the duration of the monitoring period;
- I agree to avoid changing the equipment set-up as installed by the advisor for the duration of the four weeks;
- I acknowledge that data will be used by the lead researcher and academic staff of the University of Pretoria for the purposes of this research and may be used by other academic researchers in the future for the purposes of research and/or training. No personal information will accompany the usage data.

Please sign the consent form below.

I, ____, have read and understood the purposes of this study.

Participant

Signed:____ Date:________________________________

Name in print:____

Researcher

I have explained the study to the participant, and provided him or her with a copy of the participant information sheet.

Signed:____ Date:________________________________

Name in print:____

Audit No. ____________________

A.3.2 Interview consent

Department of Electrical Electronic and Computer Engineering
Hatfield, 0002, Pretoria
E-mail: setlhaolo@tuks.co.za, dsetlhaolo@gmail.com

Lead researcher: Ditiro Setlhaolo

Contact number: 084 543 2770, e-mail: dsetlhaolo@gmail.com

Consent form – Interview

Please note: The University of Pretoria will not be held liable for any damages or injuries incurred during participation in this project.

Please read the participant information sheet carefully before committing to participate in this study.

I understand that there are no risks involved in this study and that I am free to withdraw from this study at any stage of the research.

By signing this form I acknowledge and agree to the following:

- I agree to participate in the interview as part of this research;
- I agree that the interview may be recorded;
- I understand that the information will be used for research and educational purposes;
- I acknowledge that no personal information will accompany the transcriptions of the interview;
- I understand that an audit number will be used to identify me for analysis and publication purposes; and
- I acknowledge that data will be used by the lead researcher and academic staff of the University of Pretoria for the purposes of this study and may be used by other academic researchers in the future for the purposes of research and/or training. No personal information will accompany the usage data.

Please sign the consent form below.

I, ____, have read and understood the purposes of this study.

Participant

Signed:____ Date:________________________________

Name in print:____

Researcher

I have explained the study to the participant, and provided him or her with a copy of the participant information sheet.

Signed:____ Date:________________________________

Name in print:____

A.4 QUESTIONNAIRE

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Audit No.:____________________

HOUSEHOLD ENERGY CONSUMPTION QUESTIONNAIRE

Section A: HOUSING CHARACTERISTICS

1. This house/flat is ☐ Rented ☐ Owned

2. How long have you been living in this house? ☐ Less than 1 year ☐ More than 1 year

3. Dwelling size and member status

Dwelling size			**Accommodation type**	**(√)**
How many bedrooms?			Flat or apartment in a block of flats	
How many living rooms?			Cluster house in a complex	
How many floors?			Semi-detached house	
Studio	yes	no	House on a separate yard	
How many square metres is the house/flat?				

4. Household member status and highest education level

Member status	**(√)**	**Highest education level**	**(√)**
Total No. of occupants		Primary	
No. of adults		High school	
No. employed		College and above	
Retired			
unemployed			
student			
Non-school going children			
Gender			

5. Total household gross monthly income and money spent on electricity. (√)

Income		**Electricity cost**	
NONE		NONE	
Less than R3,000		R1 - 300	
3,001-9,000		R301 - 400	
9,001-13,000		R401 - 800	
13,001-20,000		R801 – 1 200	
More than 20,000		R1 201 – 2 000	
DON'T KNOW		More than R2,000	
		DON'T KNOW	

6. Do you operate a home-based business or service? ☐ Yes ☐ No

7. Any of the following energy conservation measures available in the house?

6.1	NONE		
6.2	CFL bulbs	Yes	no
6.3	Solar technology	Yes	no
6.4	Geyser insulation	Yes	no
6.5	Geyser timer	Yes	no
6.6	Smart meter	Yes	no
6.7	DON'T KNOW	Yes	no

8. On a typical week day is there someone at home all day? ☐ Yes ☐ No

9. On a typical weekend is there someone at home all day? ☐ Yes ☐ No

Section B: KITCHEN APPLIANCES

Which categories shown best describes, on average, how often you use your kitchen appliances?

Once a day	1	More than once a day	2	Between once a day and once a week	3	Once a week	4	Never	5

Appliances	**How many in the house?**	**How long have you been using it?**	**Frequency of use as above (1,2,3,5)**	**Not applicable**
1. Electric stove *Plates (state the number)* ☐ small ☐ Medium ☐ large				
2. oven				
3. Grill				
4. Microwave *Mostly used for* ☐ Cooking ☐ Warming ☐ defrosting ☐ making tea				
5. Bread maker				
6. Slow cooker				
7. Blender				
8. Sandwich maker				
9. Coffee maker				
10. Kettle				
11. Toaster				
12. Refrigerator *Type* ☐ side-by-side doors ☐ top-and-bottom doors ☐ Combined Fridge/Freezer				
13. Deep Freezer				
14. Any other electricity consuming kitchen appliances				

Section C: OTHER APPLIANCES

Once a day	1	More than once a day	2	Between once a day and once a week	3	Once a week	4	Never	5

Appliances	**How many in the house**	**How long have you been using it?**	**Frequency of use (1,2,3,5)**	**Not applicable**
1. Dishwasher				
2. Washing machine *Type* ☐ Top loader ☐ side loader ☐ Combined wash/dry				
3. Separate dryer				
4. Iron				
5. Hair dryers				
6. Computer				
7. Laptop				
8. Printer				
9. Fax machine				
10. Stereo				
11. Power drills				
12. Electric blankets				
13. Television				
14. VCR				
15. Decoder				
16. Sewing machine				
17. Any other electricity consuming appliances				

Section D: HEATING AND COOLING

Appliances	**How many in the**	**How long have you been using it?**	**Frequency of use (1,2,3,5)**	**Not applicable**

	house			
1. Space heater				
2. Air conditioner				
3. ceiling fans				
4. Portable heater				
5. Under floor heating				
6. Geyser				
7. Gas heaters				
8. Any other electricity heating appliances				

Section E: INDOOR LIGHTS

1. On a typical **weekday**, please tell me the number of **indoor lights** normally turned on for each of the following time periods. **Do not include any night lights in your count.**

Duration		Not applicable
1.1. Less than half a day		
1.2. More than half a day		

2. On a typical **weekend**, please tell me the number of **indoor lights** normally turned on for each of the following time periods. **Do not include any night lights in your count.**

Duration		Not applicable
2.1. Less than half a day		
2.2. More than half a day		

3. Are any indoor lights left on all night? ☐ Yes ☐ No

Section F: INSULATION

1. How many sliding glass doors does your home have? Count each pair of sliding glass doors as one door. Enter the number.................

2. Do you know if your ceiling is insulated? ☐ Yes ☐ No

3. Approximately, how many windows does your home have?

1-3		3-6		6-9		9-12		12-15		More than 15	

4. Overall, would you say that your home is …

Well insulated		Adequately insulated		Poorly insulation		No insulation		Don't know	

Section G: OUTSIDE THE HOUSE/FLAT

1. Do you have a **pool**?	Yes	No
1.1. Do you a timer for the pool?	Yes	No
1.2. Do you use a heater for the pool?	Yes	No
1.3. Do you use a pool cover?	Yes	No
1.4. Do you have lights for the pool?	Yes	No
1.5. Do you use energy saving lamps for pool lights?	Yes	No
2. Do you have a **garden**?	Yes	No
2.1. Do you have lights for the garden?	Yes	No
2.2. Are they energy saving lights?	Yes	No
2.3. Do you use a timer for the garden lights?	Yes	No
3. Do you have an **electric fence**?	Yes	No
4. Do you have **electric gate**?	Yes	No

Section H: MISCELLANEOS

1. Which advertisement method sensitizes you most when it comes to energy saving?

television		radio		Family and friends		flyers		seminars	

2. Refer to the following additional questions for further information.

2.1.	Do you normally switch off appliances at the wall that are not in use?	Yes	No
2.2.	Do you sometimes leave appliances on stand-by?	Yes	No
2.3.	Do you know if your geyser has reduced temperature settings?	Yes	No
2.4.	Do you normally close the fridge door quickly?	Yes	No
2.5.	Do you use hot water bottles	Yes	No
2.6.	Does your house/flat have window shutters?	Yes	No
2.7.	Do you know if your geyser uses a timer?	Yes	No
2.8.	Do you have a shower?	Yes	No
2.9.	If so, does it use water saving shower heads?	Yes	No
2.10.	Do you have special curtains that you use to control temperature in the house?	Yes	No

3. On a scale of 1-5 as shown below, kindly state with a (√) your level of inconvenience in participating or implementing energy saving activities in your house.

1	2	3	4	5
No inconvenience	Slight inconvenience	Neutral	inconvenienced	Highly inconvenienced

		Answers				
		1	**2**	**3**	**4**	**5**
3.1.	Switching geyser off					
3.2.	Replacing bulbs with energy saving					
3.3.	Switch off unused appliances completely					
3.4.	Switching off cell phone chargers					
3.5.	Switching off lights					

4. Which activity do you feel the most inconvenience or a challenge to cope with?

____

4.1. What is the main reason that brings this challenge?

____

5. When you see the power alert on tv, do you

1	2	3	4
Switch off something	Think of switching off something	None	Do not care

6. Which appliance comes to mind when you think of switching off something?

____

7. Any other remarks?

____

____

____

____

THANK YOU VERY MUCH FOR YOUR KINDNESS TO PATICIPATE IN THIS STUDY.